Working Paper:

Can Text Message Nudges Improve Academic Outcomes in College? Evidence from a West Virginia Initiative

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Although socioeconomic disparities in college enrollment have declined, gaps in college completion persist by income and geography. We investigate a text messaging campaign in West Virginia, which aimed to address informational barriers and behavioral obstacles by providing lower-income college students with simplified information, encouragement, and access to one-on-one advising. Using descriptive and quasi-experimental methods, we find treated students were 6-6.7 percentage points more likely to persist throughout their first year of college, with modest gains to credit completion. This evidence suggests colleges can play an important role communicating information about academic expectations, support resources, and norms.

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I. Introduction

While college enrollment has increased substantially over the past few decades, the total share of Americans with a college degree is essentially unchanged since 1980 and socioeconomic inequalities in college completion have widened over time (Aud et al, 2013; Bailey & Dynarski, 2012; Bound, Lovenheim, & Turner, 2010). These gaps in college success persist even after controlling for students' academic achievement (Belley & Lochner, 2007; Kena et al, 2015; Long & Mabel, 2012). There are also considerable geographic gaps in college attainment. Students from rural areas are more likely than their non-rural peers to come from lower-income families and, even after accounting for family income and academic preparation, are less likely than their non-rural peers to earn a bachelor's degree (Pierson & Hanson, 2015; Player, 2015). Educators and policy makers have invested significant resources to address these inequalities; historically, these strategies focused primarily on improving academic readiness and college affordability. More recently, however, researchers have investigated how informational barriers and behavioral obstacles contribute to socioeconomic and geographic disparities in college success.

Researchers have designed and evaluated, often through randomized controlled trials, a range of behaviorally informed strategies to help students navigate these critical junctures and follow through on their collegiate aspirations. These interventions include sending high-achieving, low-income students semi-customized information about high-quality, affordable colleges that might be a good match for their abilities; incorporating financial aid assistance into the income tax preparation process; and sending students personalized text messages about required pre-matriculation tasks (Bettinger et al., 2012; Castleman & Page, 2014; Hoxby & Turner, 2013).

While each of these—and other similar—interventions led to substantial increases in college entry or persistence, all were implemented while students were still in high school. By comparison, there is relatively little rigorous evidence about whether and how low-touch, behaviorally informed interventions can improve college persistence and academic success for lower-income populations once they have matriculated to colleges and universities. The current study investigates whether a text messaging campaign in West Virginia that provided lower-income college students with information, encouragement, and individualized assistance was associated with improved academic outcomes and persistence during students' first year of college. We compare ordinary least squares (OLS) and propensity score weighting (PSW) estimates to examine the relationship between intervention participation and student outcomes. To preview our results, we find that on average, treated students were 6-6.7 percentage points more likely to remain enrolled throughout their first year of college completed an additional credit their first year relative to students who never received an invitation to participate in the intervention. This increase in persistence was larger for students from rural areas, around 7.6 percentage points.

We organize the remainder of our paper as follows. In Section II, we review extant literature and theory around higher education persistence as well as the role of behavioral sciences in addressing student barriers to college persistence. Section III describes the intervention in detail. In Section IV, we describe our research design, including the data, sample and our empirical strategy. In Section V, we present our results for students' academic outcomes and in Section VI we discuss the content of students' text message interactions with counselors. In Section VII, we conclude with a discussion of these findings and their implications for policy, practice, and further research.

II. Review of the Literature

This study draws on prior research in college access and persistence, focusing on literature addressing the challenges low-income and rural students face, as well as a broad literature on the role of behavioral science interventions in guiding students' engagement with the postsecondary sector.

College Access and Persistence among Low-Income and Rural Students

We frame our study in the broader human and social capital frameworks of educational investment (Becker, 1964; Perna, 2006). Becker's (1964) theory argues that individuals determine a level of educational investment based on the direct and indirect costs of attainment and the long-term benefits of an investment. These evaluations of costs and benefits and decision-making processes take place in the context of many student-level factors, such as socioeconomic status, race, or geographic location that may influence how individuals value different costs and benefits (Perna, 2006). Specifically, lower-income, first-generation, and rural students often lack access to social capital and professional assistance in their communities to navigate these decisions, and while their parents often want to help, they may lack the personal experience or confidence to do so (Coleman, 1988; Lareau, 2003; Pascarella, Pierson, Wolniak, & Terenzini, 2004). After arriving on campus, students from marginalized and underrepresented groups may experience culture shock and given unfamiliarity with the "rules" of college may struggle to succeed (Bourdieu & Passeron, 1977; Walton & Cohen, 2007).

Evidence suggests that students' socioeconomic status, geographic background, and first-generation status often intersect, and one identity can moderate the way another identity relates to educational attainment. Rural students are more likely to have economic disadvantages compared to their non-rural peers (Adelman, 2002; Lichter & Jonson, 2007). Socioeconomic background is certainly a predictor of college attendance for students from rural areas, but the availability of family and community social capital and connections to their hometown also strongly predicts rural students' college pursuit (Smith, Beaulieu, & Seraphine, 1995; Byun, Meece, & Irvin, 2012). Rural students often feel a stronger connection to their hometown, and are either reluctant to move away from family or face pressure from family and community members to remain geographically close (Beasley, 2011; Petrin, Schafft, & Meece, 2014; Means, Clayton, Conzelmann, Baynes & Umback, 2016). Low-income and first-generation students are each less likely to persist through college than their more advantaged peers, and the intersection of socioeconomic and first-generation status is associated with even lower rates of eventual BA completion (Engle & Tinto, 2008). These gaps in college persistence and completion along many student identity dimensions point to the need for multifaceted interventions to support students' unique needs.

Behaviorally Informed Interventions Promoting College Success

Given gaps in access to social capital and professional support for college application and matriculation decision-making, in the face of complexity, students may put off completing important tasks or making a decision and miss key deadlines; use simplifying strategies to decide where to apply or enroll (e.g., choosing a college that has nice dorm rooms); or stick with the status quo rather than making an active choice (Castleman, 2015a; Thaler & Sunstein, 2009). These behavioral responses can result in students not applying to well-matched colleges, completing financial aid applications, or successfully matriculating in college (Bettinger et al, 2012; Castleman & Page, 2014; Hoxby & Avery, 2012; Hoxby & Turner, 2013). Just at students face behavioral barriers to successful college matriculation, they also encounter obstacles persisting through college. For example, many students in good academic standing who would likely receive continued aid fail to refile the FAFSA and, as a result, are more likely to drop out of college (Bird & Castleman, 2016).

The theory of action underlying texting campaigns is that complex information can be broken down into concise, digestible portions, and delivered to students at relevant times in their college trajectory, through a communication channel that most young people engage with on a daily basis (Lenhart, 2012). Texts also have the unique advantage that they are accompanied by alert notifications by default (i.e., phones chirp or vibrate when people get a text), so each message captures students' attention, at least for moment in time. Researchers can leverage this attention-grabbing feature of texts to nudge students to complete important actions before their attention is diverted elsewhere (Karlan et al., forthcoming). Moreover, text message campaigns can be configured so that students simply have to write back to a message to connect one-on-one with a college or financial aid advisor, which substantially reduces barriers to help seeking (Karabenick and Newman, 2013).

Numerous randomized trials in education have rigorously evaluated this theory of action, and have consistently found that behaviorally informed text messaging campaigns can lead to substantial improvements in educational achievement and attainment (Behavioral Insights Team, 2016; Bergman, 2012; Castleman and Page, 2015; Castleman and Page, 2016; Kraft and Rogers, 2014; York & Loeb, 2014). Two prior studies in higher education include an RCT evaluation of a private college coaching program that offered phone-based coaching for college freshmen and a text messaging intervention that reminded college freshmen to renew their financial aid (Bettinger & Baker, 2013; Castleman & Page, 2016). Both studies found that strategically timed "nudge" messages and advising can lead to improved persistence in college.

Our paper extends prior research in several important ways. First, most of the prior nudge research in education has been implemented by high schools, community-based organizations, or for-profit entities.

While other studies have examined college outreach to current students and applicants about specific financial aid deadlines (ideas42, 2015; Castleman, Meyer, Sullivan, Hartog, & Miller, 2017), ours is the first study of which we are aware to investigate a texting campaign in which colleges actively reached out to students about a range of deadlines and academic support opportunities via a low-touch texting campaign. This focus on the role of higher education institutions is important given national calls (including a White House Summit in 2014) for colleges and universities to more proactively contribute to reducing socioeconomic disparities in higher education. Second, we are able to observe a richer set of outcome measures than prior studies, which have primarily focused on coarse measures of persistence from one term to the next. Using data from WVHEPC, we investigate the relationship between texting campaign participation and specific academic outcomes in college, including the number of credits students attempt and complete and their first-year GPA.

Finally, most prior work has focused on the impact of nudges on urban student populations, yet rural students face arguably greater barriers to accessing professional advising given how geographically distant they often are from school- or community-based supports. In a survey of West Virginia high school seniors intending to go to college, the top problems faced by students in their college pursuit were a lack of financial resources and lack of information about college in general and financial aid more specifically (Chenoweth & Galliher, 2004). Individuals living in rural areas are also less likely to own a smartphone as their primary phone, bringing to question whether text messaging interventions – which often utilize embedded links to services and resources – would have the same positive effects as they have in urban settings (Smith, 2013). Our paper provides valuable evidence of how students living in rural areas respond to and engage with mobile-based strategies to improve college outcomes.

III. Intervention Overview

Intervention Development

The West Virginia Higher Education Policy Commission (WVHEPC) oversees public policies related to the public four-year colleges and universities within West Virginia. WVHEPC provides support and assistance to individual colleges and universities and pursues several statewide initiatives aimed at improving college access and success for students in the state. These include concrete resources like the College Foundation of West Virginia college web portal, through which students can apply to college and access college and career planning resources, as well as awareness campaigns such as the "15 to Finish" initiative, which encourages students to take 15 credits each semester to reduce the time it takes to earn a degree.

In fall 2013, WVHEPC received a grant from the Kresge Foundation to design and implement a text messaging campaign to support seniors in the state to transition to and succeed in college. WVHEPC designed the text campaign to address several reasons why even college-intending students may not complete important college-related tasks, based on a prior texting intervention (Castleman, 2015a; Castleman, 2015b; Castleman & Page, 2015; Castleman & Page, 2016). First, the campaign targeted information asymmetries. Results from a survey of West Virginia students during the 2012-13 academic year showed that 34 percent of 11^{th} and 12^{th} grade students did not know what the FAFSA was, and 54 percent either hadn't thought about completing a college application, or felt uncomfortable about their knowledge of what to do and where to find help (WVHEPC, 2013). Even students who are aware about what tasks have to be completed may not manage their time effectively or put off these tasks in favor of more immediate demands, and miss important deadlines. A seminal behavioral science experiment found that sharing a map to the student health clinic was the most effective outreach approach to increase students' take-up of tetanus shots – not because students did not know where the clinic was, but because the map made students think through a plan of action to get their shots (Leventhal, Singer, & Jones, 1965). This campaign similarly worked to provide prompts and salient information about college enrollment deadlines and post-matriculation resources such as advising hours or the writing center location. Finally, students who know what tasks have to be completed and are motivated to complete them may nonetheless struggle with the complexity of tasks such as applying for financial aid renewal or evaluating loan options. The campaign provided resources and offered encouragement to help students navigate decision-making. Messages were also personalized to students, and invited students to write back if they needed assistance from a college advisor.

Intervention Timeline

WVHEPC implemented a pilot texting campaign during the 2013-14 academic year, and then rolled out to additional high schools in 2014-15 and statewide in 2015-16. Table 1 notes the number of high schools included in our analytic sample for the first two years of implementation – the program included 14 target and 14 comparison high schools in 2013-14 and 32 target and 26 comparison high schools in 2014-15. All students from the targeted high schools who consented to receive texts were enrolled in the WVHEPC text messaging campaign. Due to data limitations, we only observe information for students attending target and a set of comparison high schools in a given implementation year who subsequently enrolled in a public, two- or four-year West Virginia institution; table 1 includes counts of how many students enter our analytic sample from target and comparison schools each year.

The Commission broadly publicized the text campaign within target high schools, and students had various avenues through which they could sign up: they could opt in to messages on their college applications, during "College Goal Sunday" FAFSA workshops, and while applying for the state "PROMISE" merit-based scholarship application. Student opt-in dates ranged from mid-December to mid-April, with about 91 percent of students who signed up for the campaign doing so by the end of December. More than half of the students in our sample who matriculated to college initially signed up for the campaign while completing the PROMISE application (53 percent), with the next most frequent sign-up method being while completing an application to one of the state's four-year institutions (25 percent).

WVHEPC continued to message students during the summer after high school and into the first year of college. While this intervention mirrors prior texting interventions, an important novelty of the WVHEPC campaign was that the Commission actively engaged with a set of "partner" colleges and universities in the state that enroll a large number of West Virginia high school graduates. Among the population of high school seniors that participated in the high school campaign and decided to attend one of these institutions, colleges supplemented WVHEPC outreach with their own institution-specific text messages. Partner institutions messaged students who opted-in about financial aid and required pre-matriculation tasks during the spring of senior year in high school, and some continued to message these students during the summer after high school and into the first year of college. First year messages encouraged students to make use of campus-based resources, such as academic advising and tutoring; to register for courses in advance of each term; and to re-apply for financial aid. An additional set of messages provided more general encouragement and affirmation for students during their transition into college.[1]

Upon matriculating in college, most students received messages approximately 1-4 times a month on topics ranging from meeting with an academic advisor and the availability of tutoring to financial aid renewal and course registration for the next term. Since our analytic sample is limited to college matriculants, our analyses focus on the relationship between texting college freshmen and their first-year academic success.

Intervention Evaluation

We present in this paper a descriptive comparison of texted and non-texted students' first-year college outcomes. We incorporate several different comparison groups into our analyses to test the sensitivity of our estimates; our preferred comparison group is drawn from the population of college matriculants who attended high schools that are very similar to the target high schools, but where students did not have the opportunity to sign up for the texting campaign. We also employ propensity score weighting to account for self-selection into treatment and test the sensitivity of our results to different models.

III. Research Design

Sample

Our sample includes students who immediately enrolled in a West Virginia public two- or four-year institution after graduating from target and comparison high schools selected by WVHEPC. As displayed in Table 1, this includes 1,284 students from the 2014 cohort and 2,480 students from 2015 cohort. No students from comparison high schools received an invitation to participate in the intervention; at target high schools, some students signed up for the intervention and some did not. We hypothesize that

[1] Message templates available upon request

students within the target high schools who did and did not sign up for the intervention were likely to differ systematically on important observable and unobservable characteristics that would bias any findings. Table 2 bears out this hypothesis.

In the first column of table 2 we present average observable characteristics for students who signed up for texting. The second column shows the difference in characteristics for students in target schools who did not sign up for texting, and the third column shows the difference in characteristics between treated students and students from comparison schools who were not offered texting. Students who did and did not sign up for the intervention was significantly different on many measures. Treated students are more likely to be female, have higher average high school GPAs, have higher ACT scores, more likely to have complete GPA and ACT records, and are less likely to be economically disadvantaged (measured as having an EFC of $0). However, students from comparison high schools are much more similar on average to treated students – the only significant difference is that comparison high school students are less likely to have an EFC of $0 (one significant difference out of ten measures).

Given the greater similarities on observable characteristics displayed in table 2, we focus our analysis on differences in outcomes between students who opted in to receive the informational messages and students from comparison high schools who were not offered the opportunity to sign up for the text messaging campaign.[2] Across the two cohorts, this includes 1,277 treated students from target high schools and 1,683 non-treated students from comparison high schools (a total analytic sample of 2,960).[3]

WVHEPC selected the comparison schools used for our analysis, initially in 2013-14 using a set of comparison schools identified for an analysis of the target schools' GEAR UP program through propensity matching. In table 3, we show average school-level characteristics for target and comparison high schools separately for each year in our analysis (the 2013-14 pilot year and the 2014-15 rollout year). Using information from the Common Core of Data (CCD) and the Federal Student Aid (FSA) offices of

[2] See Clark, Scafidi, and Swinton (2012) for a similar approach examining end-of-course outcomes for students participating in Advanced Placement (AP) courses compared to students at schools not offering that AP course.
[3] We also ran analyses using all non-treated students as the comparison and just non-treated students from target schools as the comparison. We present findings from different comparison group specifications in appendix table 1.

the U.S. Department of Education, we observe that target and comparison schools were similar in terms of overall enrollment, 12th grade enrollment, percent of white and black students, rurality, and 12th grade FAFSA filing. Target schools were much more likely to have community eligibility for their school lunch program and thus have all students eligible for free- or reduced-price lunch (FRPL); however, FRPL eligibility was still quite high among the comparison schools (51 percent in 2013-14 and 48 percent in 2014-15).

Data and Measures

We use three primary data sources for our analysis. First, we identified college matriculants who participated in the text campaign based on data from Signal Vine, the texting platform with whom WVHEPC contracted to send the messages. The Signal Vine data indicate whether a student signed up for text messaging, as well as when and how he or she signed up. We then merged that information onto a dataset of college-going students in the state for the 2014 and 2015 cohorts provided by WVHEPC for the target and comparison high schools and Common Core of Data (CCD) school-level records to identify students' rurality.[4]

The WVHEPC data includes each student's high school, race/ethnicity, gender, ACT total and sub-section scores, SAT math and verbal scores, high school GPA, FAFSA filing status, expected family contribution (EFC), and birthdate. We used concordance tables to convert all SAT scores into ACT scores since the majority of students in our sample took the ACT (more than 90 percent of our sample report ACT scores).[5][6] As mentioned above, our available outcomes of interest are fall and spring courses attempted and completed and semester GPA for students' first year of college. Availability of spring outcomes is contingent on students remaining in the data sample between the fall and spring semesters.

[4] We measure rurality as whether the CCD indicates a target or comparison high school is "Rural – Distant, Fringe, or Remote." We acknowledge this school-level measure likely masks variability in the rurality of students attending a given school, but is the closest measure of rurality we were able to obtain.
[5]ACT/SAT concordance tables: https://www.act.org/solutions/college-career-readiness/compare-act-sat/
[6] About seven percent of students in our sample do not have an ACT or SAT score and less than a percent of students are missing a high school GPA. We code missing values as zero and include indicators for missingness in our models.

Empirical Strategy

We used ordinary least squares (OLS) regression to estimate the relationship between the text campaign participation and students' academic outcomes during their first year of college. Our basic model is as follows:

$$Y_i = \beta_0 + \beta_1 Treat_i + \beta_2 X_i + \lambda_t + \varepsilon_i$$

where *TREAT* represents whether or not student *i* opted in to the texting treatment and X_i is a vector of all the available student-level covariates including race, gender, high school GPA, ACT score, whether students filed the FAFSA, whether students had an expected family contribution (EFC) of $0 from the FAFSA, and rurality.[7][8] We also include a cohort/year fixed effect (λ_t) and cluster robust standard errors by high school.

Our primary modification to the core model is to allow the relationship between the texting campaign and students' outcomes to vary by whether the students' colleges sent institution-specific information and encouragement. Prior research suggests both that students may be more responsive to outreach from their own college, and that students may be more responsive to information that is personalized and salient to their personal circumstances (Castleman, 2015a; Castleman, Schwartz, and Baum, 2015; Castleman, Owen, and Page, 2014). We examine whether this is the case for students enrolled in the schools that collaborated with WVHEPC to send frequent, additional text messages with school-specific information. For example, these "partner" schools sent messages like *"First days at XX – what to do: orientation, campus map (<link>), buy books (<link>), meal plan selection (<link>)."* The WVHEPC messages shared generic encouragement, like *"Hi [student name]! We can't wait to see you on campus! All set for freshman year? Contact us if u need any last minute help! Txt back or call."* We also explored heterogeneous relationships by students' family income and students' rurality.

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[7] The student sample in this state is racially homogenous, with almost 93 percent of the sample identifying as White. Given this limited variation, we collapsed race/ethnicity categories into a binary White/non-White variable.

[8] We run models including and excluding student characteristics and neither point estimates nor precision vary substantially or consistently (e.g., a mix of smaller and larger point estimates obtained by omitting covariates). Appendix table 2 reports the main treatment point estimate obtained from equation (1) for models with and without covariates.

We compare our results from the OLS analysis to estimates using a propensity score weighting (PSW) approach. This approach uses the likelihood for an individual to take-up treatment to create a balanced sample in terms of baseline covariates (Austin, 2011). We first estimate the likelihood of each individual opting into the texting campaign using a logit model, and including student-level characteristics measured prior to the offer of treatment:

$$TREAT_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

where *TREAT* represents the observed variable indicating whether or not student i was actually treated and X_i is a vector of all pre-treatment student-level covariates available (student race, gender, ACT score, high school GPA, whether students filed the FAFSA, whether students have an EFC of $0, and rurality). In addition to including variables due to availability, we also draw on prior research on the relationship between these variables and both treatment take-up and college outcomes to motivate inclusion (Noble & Sawyer, 2002; Fan & Nowell, 2011; Heckman, Ichimura, & Todd, 1998). We ran the model separately for each cohort. The model then predicts a propensity score indicating the likelihood that an individual would have been treated, based on the observed covariates in our model.

We then re-ran our OLS models including probability weights. The use of inverse probability of treatment weights (IPTW) enables us to adjust the non-treated sample to better approximate the treated sample in the distribution of observable characteristics included in our propensity score estimation models (Morgan & Todd, 2008). Weights rely on the following equation, where Z_i represents whether or not a student is actually treated and e_i represents each individual's propensity score:

$$w_i = Z_i + \frac{(1 - Z_i)e_i}{1 - e_i}$$

Each student i is assigned a weight (w_i) equal to 1 if the student is treated or the inverse probability of treatment if the student is non-treated. That is, non-treated students with a probability of treatment greater than 0.5 receive weights greater than 1 and non-treated students with a lower probability of treatment have weights less than 1 (Morgan & Todd, 2008; Austin, 2011). Table 4 compares balance on student-level covariates for our non-weighted OLS models and the PSW models for our prefered comparison group (column 1 replicates column 3 from Table 2). While we have good balance on covariates in our basic OLS models, our weighted sample of treated and comparison students are even more similar on observeable characteristics.

Limitations

The main limitation in our analysis is our inability to identify a causal relationship between treatment and student outcomes. Students signed up for the treatment, and the observable and unobservable characteristics which determined sign-up likely also affected their college engagement and persistence, even absent treatment. Because students were not randomly assigned to the first year messaging campaign, we are unable to make causal claims about the campaign's effectiveness. Nonetheless, given limited prior research on informational nudge strategies with college students or in rural settings, our descriptive investigation—using ordinary least squares regression to estimate the relationship between participation in the texting initiative and students' academic outcomes—provides valuable early evidence to guide research, policy, and practice. We attempt to address this limitation by using a comparison group more similar on observeable characteristics to treated students, including student- and school-level covariates in our estimation models, and comparing our regression results to our propensity weighting results. We reiterate that we cannot make causal claims about the intervention as a result of this analysis, but believe our descriptive investigation provides valuable insight into the application of digital advising on students' college outcomes.

IV. Results

Our analysis examines three sets of outcomes – intensity of enrollment (credits attempted and completed), academic performance (semester GPAs), and first-year persistence (fall-to-spring retention). For each outcome, we examine the basic treatment difference, as well as heterogeneity in outcomes for students enrolled at high-text "partner institutions" that sent school-specific messages, for low-income students (who have an EFC of $0), and for rural students. For comparison, we include in each table the average outcome for non-treated students; in the cases of heterogeneous differences, we present the average outcome for non-treated students with the same characteristics (e.g., non-treated low-income students and non-treated students enrolled at a partner school).

We display results chronologically through the first year of college, examining fall semester credits attempted, completed, and GPA in table 5. Our analysis suggests that students who received the intervention attempted about 0.19 additional credits their first semester, but did not significantly differ from their peers in terms of fall credits completed or GPA. We observe larger point estimates for low-income and rural students participating in the intervention. Treated low-income students attempted an additional 0.3 credits compared to their non-treated peers, and treated students from rural high schools attempted an additional 0.2 credits relative to their non-treated peers. While treated students at the high-texting "partner colleges" did not have significant differences in credits attempted or completed, they did earn significantly higher GPAs – the average GPA for non-treated students at partner schools was a 2.33, and treated students at those institutions earned GPAs about 0.19 points higher.

Turning to persistence, we observe significant overall differences in fall-to-spring retention for students who participated in the intervention. As shown in table 6, overall treated students are 6.7 percentage points more likely to remain enrolled in school throughout their first year. The heterogeneous differences for treated low-income students and students at partner colleges were smaller but still statistically significant, at 4.6 and 5.2 percentage points respectively. The point estimate for rural students was larger, with persistence rates 7.6 percentage points greater than the average retention for students from rural high schools who did not receive the intervention, around 81 percent.

Likely related to an increase in college persistence for treated students, we observe in table 7 significant overall differences in all three spring semester outcomes, with treated students attempting 1.07 more credits, completing 0.78 more credits than their non-treated peers, and earning GPAs about 0.17 points higher than the untreated average GPA of 2.18. Point estimates for low-income students' credit attempts and completion are lower than overall estimates, although still statistically significant (about 0.85 and 0.57 credits, respectively). Students at partner colleges and from rural high schools attempted more credits than their non-treated peers but did not complete significantly more credits. Subgroup differences in spring GPA are not statistically significant.

We also ran models using propensity score weights to further account for selection, and compared the overall point estimates on treatment participation for the ordinary least squares and propensity score weighted models in table 8. We see that the point estimates for PSW models are smaller than the estimates obtained from OLS models, but, with the exception of the estimate on spring credits completed, do not vary in statistical significance. This increases our confidence in our descriptive analysis of the text messaging campaign and findings that generally students participating in the intervention realized improved college engagement and persistence relative to non-treated peers.

V. Text Interaction Analysis

In addition to examining students' outcomes, the student-level text message records allow us to explore the content of students' interactions with advisors in order to understand the mechanisms through which the intervention may have influenced student outcomes. We have text records for all students who participated in the text message campaign in high school; however, for consistency with our student academic outcome results, we only present data here on the treated students who enrolled in an in-state public university the fall following high school graduation. We were able to merge in text message records for 396 of the 403 treated students in 2014 and 543 of the 874 treated students in 2015.[9]

Table 9 details the frequency of student interactions and some of the common themes of student messages. The majority of students receiving messages wrote back at least once – about 77 percent of the 2014 cohort and 65 percent of the 2015 cohort (about 5-8 percent of students wrote in to opt-out of the intervention). On average, students who replied did so 3-4 times, with some "high frequency" texters sending in upwards of 30 messages. Many conversations were about financial aid, with 4-6 percent of students each year writing back to their advisors about financial aid, and less than three percent of students each year asking about dorms, books, or testing requirements (e.g., the SAT, ACT, Accuplacer). At the end

[9] The type of student ID used for Signal Vine record keeping each year varied, resulting in differential match rates for the 2014 and 2015 cohorts.

of the campaign, advisors sent students a prompt to respond "1-5, w '5' being incredibly helpful & '1' being not helpful at all" evaluating the helpfulness of the text messages. The average satisfaction among respondents was about 3.2 for the 2014 cohort (with 32 students responding) and 3.1 for the 2015 cohort (with 41 students responding).

VI. Discussion

In this paper, we report on a West Virginia initiative to provide students with personalized college guidance and access to one-on-one advising through an interactive text messaging campaign. The messages sent students information during high school, the summer between high school and college, and throughout the first year of college. This campaign represents the first of which we are aware to provide students with regular, continuous virtual support throughout the 18-month transition from high school to college. Due to data limitations, we focus our analyses on the portion of the campaign that targeted students who had matriculated at West Virginia public two- and four-year colleges and universities. Although we cannot make causal claims about our analysis, we find descriptive evidence indicating that students attempted and completed more credits than their non-treated peers and were more likely to remain enrolled in college throughout their first year. Treated students from rural high schools also had greater persistence rates, around 7.6 percentage points higher than the non-treated, rural average of 81 percent. Although one key component of the campaign was incorporating college-specific text messages from partner colleges, estimates for students attending those institutions are too imprecise to make claims about the relative effectiveness of this semi-customized outreach relative to general knowledge and encouragement messages. While we do not observe any consistent patterns in students GPAs, we argue that to take statistically more courses than non-treated peers and yet earn the same GPA suggests students were doing well in any additional courses and that an increase in credit taking did not negatively relate to their performance.

The findings from our paper raise a broader question about how the informational and behavioral barriers that students encounter during college and a lack of access to advising assistance to navigate difficult decisions may continue to affect students even after they move beyond their first year in college. Advising resources at broad access institutions are often quite limited, and those that do exist are often concentrated on first-year students (Scott-Clayton, 2015). Recent descriptive evidence suggests that even students who have demonstrated substantial potential for academic success in college may struggle to successfully navigate key decisions, like identifying which courses are required to complete their program of study. As many as 25 – 30 percent of students at broad institutions who completed 75 percent or more of the credits they need to earn a degree withdraw before completing their program (Mabel & Britton, 2016). Our examination of the content of students' interactions with the intervention suggests frequent inquiries about financial aid, with some discussions of testing requirements, dorm arrangements, and textbooks. Most students replied to the texting campaign at least once, averaging 3-4 replies throughout the campaign. Although this campaign is a step in the right direction toward continual support during the college transition, students might benefit from extended advising at lower frequencies at other junctions during their postsecondary careers.

Another question is how sensitive the impacts of these interventions are to the particular technological channel through which information and nudges are delivered—in this case, SMS-based text messaging. While text messaging offers several advantages as described above, the success of these campaigns is likely more a function of identifying communications channels that young people are engaging with on a regular basis and then applying behaviorally-informed principles to design and deliver information in ways that motivate engagement and informed decision making. This is likely to involve integrating messaging about important decisions and available resources into images and infographics, given the growing popularity of media-intensive platforms like Snapchat and Instagram. A growing number of large-scale messaging campaigns, including First Lady Michelle Obama's Up Next texting campaign, are beginning to use creative images infused with college and financial aid-related messaging. The effectiveness of these campaigns also relies on successful transmission of digital messages. Although there was concern that this type of campaign might not be as effective in more rural areas with reduced bandwidth access, our findings suggest that rural students were about as responsive to treatment as non-rural students.

In its current form, our paper provides the first suggestive evidence of which we are aware that low-touch, behaviorally-informed outreach to underrepresented college freshmen from rural areas can lead to improvements in students' first-year academic persistence and credit loads. These results are particularly salient as public colleges and universities across the country face a daunting challenge of supporting a growing population of non-traditional students with dwindling resources, as state appropriations to higher education continue to decline over time. Messaging campaigns offer a cost-effective strategy that colleges and universities can use to provide students with simplified information, encourage them to make use of campus-based resources, and directly connect them to advising if they need additional assistance.

TABLES

Table 1: Intervention Design & Expansion

		2013-14	2014-15
Target Schools			
	Number of Schools	14	32
	Number of Matriculants Treated	407	874
	Number of Matriculants Non-Treated	248	558
	Total College Matriculants	655	1,432
Comparison Schools			
	Number of Schools	14	26
	Number of Matriculants Treated	N/A	N/A
	Number of Matriculants Non-Treated	640	1,048
	Total College Matriculants	640	1,048
Total Analytic Sample		1,047	1,922

Notes: Table describes the initial rollout and expansion of the WV college texting intervention. In 2013-14, the state offered treatment to students at 14 GEAR UP high schools; in 2014-15 the state expanded eligibility to an additional 18 high schools in the state and provided data on additional comparison schools. Due to data restrictions, counts of college matriculants from each high school restricted to students who immediately matriculate at a public, two- or four-year college or university in West Virginia.

Table 2: Treated vs. Comparison Student Characteristics

	Treated Student Average (1)	Comparison Differential A: Treated School, Non-treated (2)	Comparison Differential B: Comparison School, Non-treated (3)
Female	0.598	-0.088***	-0.011
	(0.015)	(0.023)	(0.024)
Minority	0.063	-0.001	0.004
	(0.014)	(0.013)	(0.022)
White	0.937	0.001	-0.004
	(0.014)	(0.013)	(0.022)
HS GPA	3.372	-0.187***	-0.011
	(0.030)	(0.036)	(0.042)
Missing GPA	0.005	0.009***	-0.001
	(0.002)	(0.003)	(0.003)
ACT Score	19.609	-1.678***	0.160
	(0.359)	(0.416)	(0.510)
Missing ACT	0.063	0.060***	0.005
	(0.014)	(0.016)	(0.018)
EFC of $0	0.349	0.072**	-0.072**
	(0.020)	(0.027)	(0.034)
Filed FAFSA	0.988	-0.011	-0.010
	(0.004)	(0.006)	(0.006)
Rural	0.727	-0.044	-0.084
	(0.105)	(0.074)	(0.155)
Observations	1277	804	1683

Note: Robust standard errors clustered by high school in parentheses. Column 1 reports the average characteristic for students in target high schools who signed up for treatment; column 2 reports the difference in average characteristics between treated students and students in target high schools who did not sign up for treatment; column 3 reports the difference in average characteristics between treated students and students in comparison high schools who were not offered the opportunity to sign up for treatment. Includes cohort fixed effects.

***p<0.01, **p<0.05, *p<0.10

Table 3: Target vs. Comparison School Characteristics

	2013-14		*2014-15*	
	Target School Average	Comparison School Average	Target School Average	Comparison School Average
Total School Enrollment	574.714	531.571	626.281	536.115
	[178.610]	[159.618]	[297.594]	[297.594]
12th Grade Enrollment	127.429	115.643	135.938	109.731
	[34.404]	[40.254]	[71.405]	[71.405]
Black	0.029	0.010	0.039	0.023
	[0.052]	[0.011]	[0.072]	[0.072]
White	0.965	0.979	0.951	0.967
	[0.052]	[0.015]	[0.076]	[0.076]
Rural	0.929	0.857	0.719	0.692
	[0.267]	[0.363]	[0.457]	[0.457]
NSLP Community Eligibility	0.929	0.214***	0.594	0.269**
	[0.267]	[0.426]	[0.499]	[0.499]
FAFSA Filing, March 2014	0.447	0.400	0.434	0.465
	[0.107]	[0.090]	[0.097]	[0.097]
Number of Schools	14	14	32	26

Notes: Standard deviations in brackets. Tests for differences by treatment status within each year. Data from the Common Core of Data 2013-14 school year with the exception of FAFSA filing obtained from the Federal Student Aid report for March 6, 2014 weekly count of FAFSA submissions.
***p<0.01, **p<0.05, *p<0.10

Table 4: Covariate Balance for OLS vs. PSW

	OLS	PSW
	(1)	(2)
Female	0.011	0.001
	(0.024)	(0.024)
Minority	-0.004	0.001
	(0.022)	(0.020)
White	0.004	-0.001
	(0.022)	(0.020)
HS GPA	0.011	-0.001
	(0.042)	(0.041)
Missing GPA	0.001	-0.000
	(0.003)	(0.003)
ACT Score	-0.160	-0.083
	(0.510)	(0.460)
Missing ACT	-0.005	0.003
	(0.018)	(0.017)
EFC of $0	0.072**	0.008
	(0.034)	(0.033)
Filed FAFSA	0.010	-0.000
	(0.006)	(0.005)
Rural	0.084	0.006
	(0.155)	(0.145)
Observations	2960	2960

Notes: Robust standard errors clustered by high school in parentheses. Both columns report the average difference on each characteristic for students in target high schools who signed up for treatment compared to students in comparison high schools who were not offered the opportunity to sign up for treatment; column 1 displays the inverse of column 3 from Table 2 and column 2 includes propensity score weights. Includes cohort fixed effects.
***p<0.01, **p<0.05, *p<0.10

Table 5: Fall Semester Outcomes (credits attempted and completed, GPA)

	Credits Attempted				Credits Completed				GPA			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	0.185**	0.134	0.281***	0.150	0.346	0.343	0.326	0.793*	0.068	0.083	0.041	0.217**
	(0.075)	(0.086)	(0.078)	(0.146)	(0.245)	(0.251)	(0.255)	(0.447)	(0.058)	(0.058)	(0.062)	(0.086)
EFC of $0		-0.086				-0.774***				-0.173***		
		(0.108)				(0.255)				(0.053)		
EFC $0*Treated		0.164				0.010				-0.047		
		(0.139)				(0.340)				(0.076)		
Partner College			-0.194				-0.142				-0.052	
			(0.244)				(0.522)				(0.104)	
Partner*Treated			-0.252				0.180				0.146	
			(0.312)				(0.578)				(0.116)	
Rural High School				-0.128				0.368				0.161*
				(0.130)				(0.365)				(0.089)
Rural*Treated				0.051				-0.644				-0.214*
				(0.170)				(0.550)				(0.115)
Total treatment		0.298*	0.029	0.201*		0.353	0.506	0.150		0.036	0.187*	0.003
		(0.123)	(0.291)	(0.086)		(0.365)	(0.567)	(0.302)		(0.085)	(0.109)	(0.072)
Comparison mean	15.02	14.60	14.47	15.01	12.31	10.65	11.26	12.51	2.59	2.20	2.33	2.66
Observations	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960
R-squared	0.173	0.173	0.177	0.173	0.267	0.267	0.267	0.268	0.279	0.279	0.280	0.281

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. For each outcome (credits attempted, completed, and GPA), we present four models. One compares treated and non-treated students in our analytic sample, one includes an interaction for treatment and low-income status (having an EFC of $0), one includes an interaction for treatment and attending a partner college, and one includes an interaction for treatment and attending a rural high school. The total treatment row reports the linear combination of the treatment and treatment interaction coefficients for each model. All models include indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES. Comparison mean represents the non-treated average for each outcome and subgroup (e.g., non-treated low-income students in the second model for each outcome).
***p<0.01, **p<0.05, *p<0.10

Table 6: First Year Persistence

	Fall-to-Spring Retention			
	(1)	(2)	(3)	(4)
Treated	0.067**	0.077*	0.048*	0.048***
	(0.027)	(0.036)	(0.028)	(0.017)
EFC of $0		0.026		
		(0.037)		
EFC $0*Treated		-0.031		
		(0.040)		
Partner College			0.108***	
			(0.030)	
Partner*Treated			0.004	
			(0.028)	
Rural High School				-0.037
				(0.037)
Rural*Treat				0.028
				(0.043)
Total treatment		0.046*	0.052**	0.076*
		(0.022)	(0.018)	(0.038)
Comparison mean	0.83	0.81	0.89	0.81
Observations	2960	2960	2960	2960
R-squared	0.105	0.105	0.117	0.105

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. We present four models. One compares treated and non-treated students in our analytic sample, one includes an interaction for treatment and low-income status (having an EFC of $0), one includes an interaction for treatment and attending a partner college, and one includes an interaction for treatment and attending a rural high school. The total treatment row reports the linear combination of the treatment and treatment interaction coefficients for each model. All models include indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES. Comparison mean represents the non-treated average for each subgroup (e.g., non-treated low-income students in the second model for each outcome).
***p<0.01, **p<0.05, *p<0.10

Table 7: Spring Semester Outcomes (credits attempted and completed, GPA)

	Credits Attempted				Credits Completed				GPA			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated	1.073**	1.176**	0.809*	0.896***	0.782*	0.879	0.697	0.960***	0.173*	0.216*	0.156	0.161**
	(0.420)	(0.558)	(0.441)	(0.299)	(0.424)	(0.548)	(0.443)	(0.350)	(0.091)	(0.119)	(0.096)	(0.072)
EFC of $0		0.299				-0.298				-0.048		
		(0.571)				(0.495)				(0.107)		
EFC $0*Treated		-0.329				-0.309				-0.136		
		(0.605)				(0.542)				(0.122)		
Partner College			1.192**				0.284				0.138	
			(0.473)				(0.777)				(0.152)	
Partner*Treated			0.229				0.145				-0.029	
			(0.526)				(0.860)				(0.161)	
Rural High School				-0.546				-0.087				-0.018
				(0.582)				(0.541)				(0.118)
Rural*Treated				0.255				-0.256				0.018
				(0.677)				(0.693)				(0.149)
Total treatment		0.847*	1.038*	1.151*		0.570*	0.842	0.704		0.080	0.128	0.179
		(0.359)	(0.390)	(0.596)		(0.339)	(0.772)	(0.591)		(0.074)	(0.143)	(0.128)
Comparison mean	12.57	11.87	12.80	12.36	10.43	8.84	9.56	10.42	2.18	1.83	2.07	2.18
Observations	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960	2960
R-squared	0.158	0.158	0.165	0.158	0.248	0.248	0.248	0.248	0.270	0.271	0.271	0.270

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. For each outcome (credits attempted, completed, and GPA), we present four models. One compares treated and non-treated students in our analytic sample, one includes an interaction for treatment and low-income status (having an EFC of $0), one includes an interaction for treatment and attending a partner college, and one includes an interaction for treatment and attending a rural high school. The total treatment row reports the linear combination of the treatment and treatment interaction coefficients for each model. All models include indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES. Comparison mean represents the non-treated average for each outcome and subgroup (e.g., non-treated low-income students in the second model for each outcome).
***p<0.01, **p<0.05, *p<0.10

Table 8: OLS vs. PSW Estimates

	OLS	PSW
	(1)	(2)
Fall credits attempted	0.185**	0.173**
	(0.075)	(0.078)
Fall credits completed	0.346	0.291
	(0.245)	(0.250)
Fall GPA	0.068	0.057
	(0.058)	(0.061)
Fall-to-spring retention	0.067**	0.061**
	(0.027)	(0.025)
Spring credits attempted	1.073**	0.962**
	(0.420)	(0.392)
Spring credits completed	0.782*	0.669
	(0.424)	(0.402)
Spring GPA	0.173*	0.157*
	(0.091)	(0.088)
Observations	2960	2960

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. All models include indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES. Propensity score weights calculated using the same set of covariates to predict treatment (calculated separately for each cohort).

***p<0.01, **p<0.05, *p<0.10

Table 9: Text Message Interactions

	2013-14	2014-15
Frequency/Intensity of Interactions		
Percent Students Replying	76.77%	64.64%
Average Number of Replies	3.5	3.9
Maximum Number of Replies	33	28
Content of Interactions		
Percent Students Opting Out	7.83%	4.97%
Percent Students Discussing Aid	6.31%	4.24%
Average Satisfaction with Interactions: '5' being incredibly helpful	3.2	3.1
Number of Satisfaction Survey Respondents	32	41

Notes: Describes the text message interactions of 396 students in 2014 and 543 students in 2015.

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APPENDIX TABLES

Appendix Table 1: Treatment Differential for Different Comparison Groups

	Comparison Group: Non-treated at Comparison Schools	Comparison Group: Non-treated at target schools	Comparison Group: Non-treated at comparison and target schools
	(1)	(2)	(3)
Fall credits attempted	0.185**	0.170*	0.177***
	(0.075)	(0.085)	(0.061)
Fall credits completed	0.346	0.370**	0.342*
	(0.245)	(0.172)	(0.188)
Fall GPA	0.068	0.088*	0.075
	(0.058)	(0.045)	(0.045)
Fall-to-spring retention	0.067**	0.018	0.051**
	(0.027)	(0.013)	(0.019)
Spring credits attempted	1.073**	0.251	0.804**
	(0.420)	(0.230)	(0.314)
Spring credits completed	0.782*	0.384	0.671**
	(0.424)	(0.256)	(0.323)
Spring GPA	0.173*	0.108**	0.159**
	(0.091)	(0.051)	(0.070)
Observations	2960	2081	3764

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. All models include indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES. The first column represents the main results discussed in this paper, comparing treated students to non-treated peers at high schools where students never received the offer of treatment. The second column runs the same analyses using only non-treated students at target schools (individuals who were offered treatment but declined to take-up), and the third column includes both sets of potential comparisons (non-treated at target high schools and non-treated at comparison high schools).
***p<0.01, **p<0.05, *p<0.10

Appendix Table 2: Treatment Differential for Models with and without Covariates

	Model 1: No covariates included (1)	Model 2: Covariates included (2)
Fall credits attempted	0.166*	0.185**
	(0.095)	(0.075)
Fall credits completed	0.340	0.346
	(0.293)	(0.245)
Fall GPA	0.071	0.068
	(0.071)	(0.058)
Fall-to-spring retention	0.068**	0.067**
	(0.026)	(0.027)
Spring credits attempted	1.052**	1.073**
	(0.412)	(0.420)
Spring credits completed	0.771*	0.782*
	(0.446)	(0.424)
Spring GPA	0.174*	0.173*
	(0.098)	(0.091)
Observations	2960	2960

Notes: Robust standard errors clustered by high school in parentheses. Includes cohort fixed effects. Model 1 only includes a treatment indicator in addition to the year fixed effects. Model 2 adds indicators for student sex, race, ACT score, high school GPA, missing indicators for ACT or GPA, whether students completed the FAFSA, whether students have an EFC of $0, and whether students attended a rural high school as measured by NCES.

***p<0.01, **p<0.05, *p<0.10