EdWorkingPaper No. 20-242

Conditions under which college students can be responsive to nudging

Lindsay C. Page
University of Pittsburgh

Jeonghyun Lee
Georgia Institute of Technology

Hunter Gehlbach
Johns Hopkins University

Success in postsecondary education requires students to engage with their institution both academically and administratively. As with the transition to college, administrative requirements students face once enrolled can be substantial. Missteps with required processes can threaten students' ability to persist. During the 2018-19 academic year, Georgia State University implemented an artificially intelligent text-based chatbot to provide proactive outreach and support to help undergraduates navigate administrative processes and take advantage of campus resources. A team of centralized university administrators orchestrated outreach "campaigns" to support students across three broad domains: (1) academic supports; (2) social and career supports; and (3) administrative processes. We investigate GSU's implementation of this persistence-focused chatbot through an experimental study. Of the three message domains, outreach was most effective when focused on administrative processes, many of which were time-sensitive and for which outreach could be targeted specifically to students for whom it was relevant based on administrative data. In contrast, outreach to encourage take up of other supports had little effect on student behavior. By the end of the academic year, rates of FAFSA filing and registration for the subsequent fall semester were approximately three percentage points higher, suggesting positive effects on year-to-year college persistence. The positive effects on fall enrollment persisted into summer 2019, at which time the GSU administration judged that the study results were compelling enough to conclude the experiment and roll the chatbot system out to all students. We situate our findings in the literature on nudge-type efforts to support college access and success to draw lessons regarding their effective use.

VERSION: June 2020

Suggested citation: Page, Lindsay C. , Jeonghyun Lee, and Hunter Gehlbach. (2020). Conditions under which college students can be responsive to nudging. (EdWorkingPaper: 20-242). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/vjfs-kv29

Conditions under which college students can be responsive to nudging

Lindsay C. Page[1]
University of Pittsburgh

Jeonghyun Lee
Georgia Institute of Technology

Hunter Gehlbach
Johns Hopkins University

June 10, 2020

Abstract

Success in postsecondary education requires students to engage with their institution both academically and administratively. As with the transition to college, administrative requirements students face once enrolled can be substantial. Missteps with required processes can threaten students' ability to persist. During the 2018-19 academic year, Georgia State University implemented an artificially intelligent text-based chatbot to provide proactive outreach and support to help undergraduates navigate administrative processes and take advantage of campus resources. A team of centralized university administrators orchestrated outreach "campaigns" to support students across three broad domains: (1) academic supports; (2) social and career supports; and (3) administrative processes. We investigate GSU's implementation of this persistence-focused chatbot through an experimental study. Of the three message domains, outreach was most effective when focused on administrative processes, many of which were time-sensitive and for which outreach could be targeted specifically to students for whom it was relevant based on administrative data. In contrast, outreach to encourage take up of other supports had little effect on student behavior. By the end of the academic year, rates of FAFSA filing and registration for the subsequent fall semester were approximately three percentage points higher, suggesting positive effects on year-to-year college persistence. The positive effects on fall enrollment persisted into summer 2019, at which time the GSU administration judged that the study results were compelling enough to conclude the experiment and roll the chatbot system out to all students. We situate our findings in the literature on nudge-type efforts to support college access and success to draw lessons regarding their effective use.

[1] lpage@pitt.edu; jonnalee@gatech.edu; gehlbach@jhu.edu. We gratefully acknowledge Georgia State University and especially Dr. Timothy Renick and C. Lindsey Fifield for their support and engagement with this study. In addition, we gratefully acknowledge members of the AdmitHub team for their insights and feedback. We thank the Michael and Susan Dell Foundation (MSDF) for providing financial support to make this research possible, and we acknowledge both MSDF and the ECMC Foundation for their financial support of project implementation. All errors are our own, and this paper does not reflect the opinions of Georgia State University, AdmitHub, the Michael and Susan Dell Foundation or the ECMC Foundation.

Conditions under which college students can be responsive to nudging

Lindsay C. Page, Jeonghyun Lee, Hunter Gehlbach

INTRODUCTION

Among recent cohorts of US high school graduates, the majority pursue some form of postsecondary education. Of those who enter higher education, however, a large share exit with no postsecondary degree or credential. Given the rising tide of income inequality in the United States, differences in degree attainment by socioeconomic status are particularly concerning. Not only are students from wealthier backgrounds more likely to access higher education than their less well-off counterparts, but conditional on enrollment, they are also more likely to complete. The Educational Longitudinal Study of 2002 reveals that approximately three-quarters of students from high-SES backgrounds, but only about half of students from low-SES backgrounds, earn a degree or credential within eight years of high school completion. In fact, for college entrants from low-income backgrounds, obtaining some postsecondary education but earning no credential is the modal outcome (Kena et al, 2014). With the steadily rising costs of college, many low and moderate income students must borrow to attend college. If these students are entering but not completing college, income inequality can be further exacerbated by the acquisition of college debt without the labor market payoff of a college credential.

One explanation regarding the worsening patterns of college degree attainment outcomes argues that students are entering higher education less academically prepared for the rigors of college-level work. Although academic readiness plays a role, Bound, Lovenheim and Turner (2010) argue that diminishing institutional resources (driven by forces like reduced state funding and increased student enrollment) are an especially important factor in declining completion rates over time. Evidence indicates that where campuses are able to invest in comprehensive supports to undergraduates from low-income backgrounds, persistence and degree attainment outcomes can be improved (e.g., Clotfelter, Hemelt & Ladd, 2018; Weiss, Ratledge, Sommo & Gupta, 2019). Of course, such programmatic investments may not be possible for resource-constrained campuses, especially as they confront the realities of the COVID-19 pandemic. This context raises the important question of whether universities might leverage low-cost, behavioral strategies to better support their students' postsecondary persistence.

Success in postsecondary education requires students to engage with their institution both academically, through their chosen degree program and associated coursework, and administratively. As with gaining admission and transitioning to college initially, administrative requirements students face once enrolled can be substantial, and missteps with required processes can threaten students' ability to continue. For example, students may lose access to financial aid by failing to (re)file the Free Application for Federal Student Aid (FAFSA) or may face monetary fines by missing administrative deadlines for enrolling in or dropping courses.

In 2016, Georgia State University implemented an artificially-intelligent, text-based chatbot to provide proactive outreach and support to would-be first-year students to navigate the required administrative processes that are specific to the college transition. Implementation was in the context of an experimental study. Throughout the summer, treatment group students received targeted outreach, reminders and the offer of support related to specific college-transition tasks, such as immunizations, transcript submission, and financial aid and registration processes. Experimental results revealed that the GSU-committed students assigned to receive chatbot outreach were more successful with a variety of required pre-matriculation tasks and were 3.3 percentage points more likely to enroll at GSU on time (Page & Gehlbach, 2017).

This paper builds upon the initial GSU effort in two important ways. First, we extend beyond a focus on summer melt to test strategies to bolster student persistence once enrolled. Second, while the original study focused exclusively on administrative processes, we additionally investigate the impact of chatbot outreach on take up of other campus-based supports. For this study, GSU experimentally deployed their university chatbot, "Pounce," named after the campus mascot, to improve student success with required processes and access to and take up of various campus resources throughout the 2018-19 academic year. A team of centralized university administrators orchestrated outreach "campaigns" to students across three broad domains: (1) academic supports; (2) social and career-related supports; and (3) administrative processes. Campaigns in the first domain pertained to general academic success. For example, messages promoted student engagement with events focused on maintaining satisfactory academic progress, participation in supplemental instruction (for students who were struggling academically), and meetings with one's academic advisor. However, the messages were not tied to specific courses or instructors. Campaigns in the second domain encouraged participation in events and other supports offered by the career services office as well as community-building events. Campaigns in the third domain dealt directly with administrative processes, many of which were time-sensitive and required for the student to remain in good standing. Topics included resolving administrative holds, handling unpaid bills, FAFSA re(filing), and registration for subsequent semesters.

Outreach was tailored to student needs where possible. General messages were sent to all students (e.g., a message providing information on the course add/drop deadline), whereas customized campaigns targeted specific students according to administrative records held by the university. For example, messages regarding registration holds were sent only to those students required to resolve holds. Similarly, over the course of the spring semester, messages regarding FAFSA filing were sent only to those students who had not yet filed.

For this study, we report experimental impacts on completion of actions specifically targeted by the outreach. In addition, we examine overall measures of student persistence and success, including term credit attainment, term GPA, and measures of continuation to the subsequent semester. To preview our key findings, the chatbot outreach was most consistently affected student behavior when it pertained to administrative processes. Specifically, the outreach was most effective when (a) targeted to those students for whom the outreach is relevant and (b) when addressing issues that are "acute," meaning that they are serious, time-sensitive or both. These include topics such as registration holds and outstanding balances that need to be resolved in order for the student to continue in good standing. Students who received chatbot outreach on these issues were significantly more likely to resolve them. In contrast, outreach related to supplemental academic, social and career-related supports, such as those that encourage students to meet with their advisors or participate in career services events, yielded little to no effect on students taking up these support opportunities at higher rates. Outreach f did not have a significant effect on overall indicators of academic success, including credit hours attempted or earned, term GPA, or graduation status by the end of Spring 2019. Nevertheless, by the end of the spring term, treatment group students were approximately three percentage points more likely to have filed the FAFSA and to have registered for the Fall 2019 semester. Therefore, the success of the tool with supporting students to navigate administrative processes – particularly those that were acute – likely may have helped students to be better positioned to continue their undergraduate careers in the following fall. The positive effects on fall enrollment persisted into summer 2019, at which time the GSU administration judged that the study results were compelling enough to conclude the experiment and roll the chatbot system out to all students.

BACKGROUND

Complex administrative processes can create barriers for student access to higher education. Research has pointed to behaviorally informed strategies to help students with navigating these processes (see Page & Scott-Clayton, 2016, for a recent review). For example, Bettinger and colleagues (2012) show that bundling the process of completing the Free Application for Federal Student Aid (FAFSA) with annual tax filing can dramatically increase student rates of FAFSA filing, access to financial aid, matriculation into higher education, and persistence in postsecondary settings. The success of this effort may be driven both by the procedural support that families received with FAFSA as well as the optimal timing of FAFSA completion at the time of tax filing. Similarly, administering college entrance exams during the school day improves college access, in effect eliminating barriers that students otherwise face in managing registration and travel processes for taking the exam on a weekend (Hurwitz, Smith, Niu & Howell, 2015; Hyman, 2017).

In addition to these efforts to reduce procedural complexity, another set of studies has taken the approach of acknowledging this complexity and testing the effect of proactive outreach and supports to "nudge" students toward task completion. Castleman and Page, for example, have tested several interventions to better support college-intending high school graduates through the administrative steps required to successfully enroll in college (Castleman & Page, 2015, 2017; Castleman, Page & Schooley, 2014) and to file or refile the FAFSA (Castleman & Page, 2016; Page, Castleman & Meyer, 2019).

More recent efforts to scale these and other nudge-type interventions or apply them to a broader range of behaviors have yielded less encouraging results. Yet, collectively these studies may help to highlight factors that are critical to the success of certain nudge strategies. A recent set of studies examined the impact of nudge outreach (delivered via a combination of text, email, and paper-based mail) on FAFSA filing or re-filing. Bird and colleagues (2019) report on a pair of experiments – one at the state level and one at the national level – to encourage FAFSA filing among high school seniors. Page and colleagues (2019) report on a national experiment implemented with a subset of students recruited for the National Postsecondary Student Aid Study of 2016 (NPSAS:16) to encourage FAFSA reapplication among college students. Across both studies, impacts on FAFSA submission and completion are modest to null. Unlike previous studies, outreach in these interventions was framed as coming from a centralized entity unrelated to the educational institutions of which students were members, with whom they had no prior relationship, and from whom they may not have expected to receive outreach. Perhaps, as Bird and colleagues (2019) suggest, successful scaling of these types of interventions needs to happen "locally," institution by institution, rather than "globally" through a centralized entity. That is, schools and colleges and universities may experience greater success in their nudge-type efforts than a centralized entity (e.g., a state agency) implementing similar outreach as a strategy in isolation.

Indeed, another pair of experiments supports the hypothesis that outreach framed as coming from a student's own institution is far more promising for affecting students' completion of key college-going tasks (Avery et al, 2020). To note is that in this paper, we observe positive effects of locally implemented outreach (e.g., outreach from an institution to its own students), although the relevant control condition in our study is no text-based outreach, rather than outreach from an entity outside of the GSU context.

Local administration may work better because students know the local organization better (providing credibility). But the reverse may also be true that the local organization may know the student better and have access to better data on where students are with required processes and what tasks they have successfully accomplished (enhancing relevance for students). By incorporating student-level administrative data into the outreach strategy, organizations can be quite targeted in their communication with students. By doing so, they increase the relevance of any communication students receive. Such data integration was possible in GSU's first chatbot experiment focused on summer melt. The availability of this process data enabled not only the targeting of outreach but also the examination of impacts on both timely enrollment and completion of the interim administrative steps required of students to matriculate on time (Page & Gehlbach, 2017).

Finally, Oreopoulos and Petronijevic (2019) report on a set of studies through which they implemented and tested nudges to move student behavior not on discrete, well-defined tasks but on more sustained behavioral change over time. Specifically, the authors tested interventions focused on (1) goal-setting; (2) mindset; and (3) coaching on how to be a successful student, all tasks with different foci, more complex components, and with longer time-horizons than the acute, discrete tasks on which we observe impacts in the current study. Across these studies, the authors emerge with a generally pessimistic view of these types of efforts for driving improvement in student academic outcomes, although they do note that the coaching interventions led to modest increases in study time as well as other non-academic outcomes such as students' feelings of support and well-being. Nevertheless, the magnitude of the effects on these intermediate behavioral outcomes was not sufficient for driving changes in overall academic outcomes such as course performance and credit attainment. These studies help to solidify an observation the authors make, that behavioral nudges may be effective when they target discrete, time-bound tasks but not nearly as effective for influencing the more sustained behavioral change over time that may be needed for driving outcomes such as academic achievement. Indeed, in the experiment on which we report here, student responsiveness to the text-based outreach that they received via Pounce was strongest when the target task was discrete, for which the consequences of inaction were clear and sometimes immediate, and for which the university had data to identify the students for whom the outreach was relevant.

INTERVENTION DESIGN

During summer 2016, Georgia State University (GSU) contracted with AdmitHub to build an artificially intelligent chatbot for the university to provide outreach and support to GSU-admitted students regarding tasks required for successful transition to GSU for the start of the Fall 2016 semester.[2] Using the AdmitHub platform, GSU texted students to remind them of required pre-matriculation tasks, provide them with step-by-step guidance on navigating tasks, prompt them to ask questions, and respond to those questions. The platform was then able to facilitate responses to students' questions. Some responses were provided to students via the system's artificial intelligence (AI). In this case, questions that matched to information in the system knowledge base were answered immediately. Where the AI could not match a question with a high enough probability of success, the question was routed, via email, to a staff member at the university for response. This response was then routed back through the AdmitHub system to

[2] For more information on AdmitHub, see www.admithub.com.

respond to the student and to update the system knowledge base. For more information, see Page and Gehlbach (2017).

Based on the success of this application of the AdmitHub tool for improving student success with pre-matriculation requirements and enrolling in GSU, the university sought to deploy Pounce to provide proactive outreach and support to GSU-enrolled students, with the goal of improving student persistence and success. The summer transition-focused implementation of Pounce could be considered relatively straightforward. The processes that students needed to complete and the associated timeline were discrete and well-defined. In addition, the consequences of inaction regarding any of the summer transition tasks was clear: students must complete them or on-time matriculation may be jeopardized. In contrast, how to use a centralized, text-based communication tool once students have matriculated is less straightforward—the number of tasks for students to complete is much greater and the key characteristics of these tasks much more heterogeneous.

During the 2018-2019 academic year, GSU chatbot implementation was overseen by a project director within the university's Office of Enrollment Management and Student Success. Further, it was supported by a full-time project associate who facilitated data gathering and management for chatbot implementation as well as project research and a full-time project administrative coordinator who monitored and triaged incoming messages on a daily basis. Under the direction of this three-person, full-time team and based on consultation with the relevant administrative offices, the university planned and deployed text-based outreach to undergraduate students from Pounce on three primary domains, as follows:

- **Academic supports.** These message campaigns aimed to raise student awareness about and participation in supports that relate to students' academic success, including attending events focused on maintaining satisfactory academic progress (SAP), participating in supplemental instruction, and meeting with one's academic advisor.

- **Social and career-related (i.e., non-academic) supports.** These message campaigns aimed to raise student awareness about and participation in events related to non-academic supports offered on the campus, including career services events and supports as well as other social, community-building events, such as a Thanksgiving feast for international students.
- **Administrative processes.** These message campaigns aimed to raise student awareness about administrative processes, many (but not all) of which were required for the student to remain in good standing with the university, including resolving holds due to an outstanding balance, FAFSA filing, resolving registration holds, and registration for subsequent semesters.

In addition to campaigns in these domains, other messages reminded students about important dates on campus, such as those corresponding to withdrawal deadlines, opening of registration for the following semester, semester breaks and holidays, exam period and when grades posted. Across campaigns, some were directed to all students, whereas others capitalized on university administrative data to target outreach only to those students for whom it was relevant. For example, campaigns related to registration holds were sent only to those students with holds to resolve. Similarly, over the course of the spring semester, messages regarding FAFSA refiling were sent only to those students who had not yet filed. In Tables 1 and 2, we provide date and topic information for all campaigns implemented. In addition, we detail whether the outreach was sent to all students or to a targeted subset. Finally, we indicate whether we report outcome data related to the behavior or action the outreach sought to encourage.

RESEARCH DESIGN

Georgia State University (GSU) is a public, four-year institution located in Atlanta, Georgia. GSU enrolls an undergraduate student body of over 25,000. Approximately half of all GSU undergraduates are from low-income families, as indicated by their receipt of a federal Pell grant. GSU implemented the persistence-focused chatbot in the context of a randomized controlled trial. At the beginning of the Fall 2018 semester, the initial study sample included 7,580 GSU students (the wave 1 sample) who were at various stages of their undergraduate career. In March 2019, the university expanded the sample by another 6,076 students (the wave 2 sample) after the implementation team judged the system ready to scale up and handle communication with additional students. Separately for each wave and within groups defined by students' year at the university,[3] we randomized students into treatment and control conditions, with approximately half of students assigned to treatment and half assigned to control. Students assigned to the treatment condition were targeted with text-based outreach from Pounce, whereas students in the control condition received business-as-usual communication from the university via other channels but not via Pounce.

Within both samples, after randomization we checked balance on a host of baseline characteristics, including indicators of student race/ethnicity, gender, financial aid status and prior academic achievement. We observed balance on all baseline characteristics, meaning that students assigned to treatment and control conditions were not systematically different from each other, on average, on any dimensions that we observed. This leads us to conclude that the randomization procedures were successful and that any subsequent differences in outcomes between the treatment and control students can be attributed to the fact that treatment students were targeted for outreach via Pounce.

We present descriptive statistics for the wave 1 and 2 samples by treatment status in Table 3. Students in the wave 1 and 2 samples are largely similar on socio-demographic features. In both, the sample is approximately 13 percent Hispanic, 45 percent Black, and 30 percent White. About one-quarter of students are first-generation college-goers, and half qualified for a Pell Grant. The sample is about 60 percent female, in line with trends of women outpacing men in college enrollment (Goldin, Katz &

[3] Specifically, for each wave, we stratified students into groups according to the following classifications: first-time freshmen in Fall 2017; first-time freshmen in Fall 2018; seniors in Fall 2018; transfers from other colleges / universities in Fall 2018; transfers from Perimeter College in Fall 2018; and all other students. Then, within each wave, we randomized students to treatment or control within these groups.

Kuziemko, 2006). Where the two waves differ is in their age and associated year in college due to most of the incoming freshmen being included in the wave 1 sample. The typical student was approximately 20 years old in the wave 1 sample and 23 years old in the wave 2 sample.

To assess the impact of assignment to the treatment on the outcomes we consider, we use fixed effects regression and linear probability models of the following general form:

$$Y_{ij} = \alpha_j + \beta \times Treatment_{ij} + \boldsymbol{X\gamma} + \varepsilon_{ij} \quad (1)$$

where for student *i* in randomization group *j*, $Treatment_{ij}$ is an indicator equal to 1 if randomized to treatment and zero otherwise, X is a vector of baseline covariates, including those listed in Table 3, and ε_{ij} represents individual error. Our key coefficient of interest, β, is an intent-to-treat effect representing the causal effect of being assigned to the text-communication treatment group on outcome Y_{ij}. In our presentation of results, we include intent-to-treat (ITT) effects estimated with and without baseline covariate controls.

Because some messages were directed to all students in the treatment group, whereas other messages were targeted only to those students for whom they were relevant, our analytic approach had to account for this differentiation. In these targeted instances, we first condition the sample on whether the message topic is relevant and then estimate the treatment effect within this conditional sample. For example, in the case of a message related to an unpaid bill, we first condition the sample on having an unpaid bill at the time of the campaign (i.e., identifying both treatment and control students with an unpaid bill) and then estimate the effect of assignment to treatment within this subsample.

Messages were not distributed to all students assigned to the treatment condition due to circumstances like opt out as well as changed cell phone numbers and students temporarily “pausing” their engagement with the chatbot, as described below. Although we cannot know for sure whether a message was received and read by a student, we can know if it was successfully distributed. Therefore, we additionally use a two-stage least squares instrumental variables (IV) approach to assess the effect of successful distribution on the outcomes of interest. In the first stage, we use treatment assignment to instrument for message distribution, and in the second-stage, we model the outcome as a function of message distribution. The IV results that we report below are from models that include baseline controls. Because distribution rates were uniformly high, ITT and IV results differ modestly, if at all, across outcomes.

RESULTS

System use and engagement

In Table 4, we present system use and student engagement metrics. In the first column, we report overall counts of outgoing (from Pounce to students) and incoming (from students to Pounce) messages. During the course of the intervention, the system distributed nearly a quarter-million messages to treatment group students. The majority of these messages were planned outreach campaigns. Another 5,000 messages were generated by the AI capabilities of the system in response to student inquiries. Nearly 800 messages to students were "triaged" responses such that a member of the chatbot team directly intervened and responded to a student inquiry, and only a handful of the messages were staff responses to messages escalated to them.[4] Across the duration of the year, students sent approximately 16,000 messages into the Pounce system. Most commonly, these were responses to closed-ended responses (e.g., answering a yes/no question), but students also sent over 5,000 open-ended questions into the system during the year. We note that the number of student inquiries escalated to staff exceeds the number of times staff responded through the system. This is because escalation to staff could prompt the staff member to reach out to the student via other modes of communication and not necessarily through the text platform.

[4] Escalation occurred when student messages were too specific or nuanced for the AI system to answer directly. In instances of escalation, the message was manually forwarded to the most relevant administrative unit among the following: Advising Office, Career Services, Financial Aid, International Student and Scholar Services, Registrar Office, and Student Success. In most cases, responses flowed back through the chatbot system in order to further update the system knowledge base.

In the remaining columns of Table 4, we present measures of average student engagement, separately by wave. Recall that wave 1 students received outreach throughout the entire 2018-19 academic year, whereas the wave 2 students were added midway through the spring term. Here, we focus our discussion on the wave 1 results and note that wave 2 results are largely consistent and reflective of outreach over a shorter duration of time. The typical wave 1 treatment student received approximately 57 outreach text messages from Pounce during the course of the intervention period. This consisted primarily of pre-planned campaign outreach messages, a small number of automatic responses provided by the AI capabilities of the system, and an even small number of messages that were sent by staff members through the system. The typical student sent approximately 3 messages into the Pounce system, with 2 of these messages being responses to close-ended survey questions and 1 being an open-ended question.

Recall that GSU sought to customize and target outreach to students using administrative data to the fullest extent possible. Given this targeting, the modest overall levels of student engagement mask substantial heterogeneity in student use of the system. For example, although many students received primarily the more general outreach directed to all students, the most engaged student received a total of 170 text messages and sent nearly 100 messages into the Pounce system during the course of the year. Of these incoming messages, the majority were open-ended questions that the system handled automatically. Further, the modest level of engagement of students through the platform can also be explained by the fact that many of the messages sought to prompt actions that required follow up with a campus office rather than communicating through the text system necessarily. As we show below, the targeted outreach was highly successful in eliciting this type of response.

Finally, when students indicated that they no longer wished to interact with Pounce, the system prompted them to text "#PAUSE" and asked them to choose if they wanted to pause outreach either temporarily for two weeks or permanently. Among wave 1 treatment-assigned students, approximately 5 percent opted out of receiving outreach from Pounce entirely and another 8 percent employed the "pause" option, whereby they requested a two-week hiatus before outreach resumed. As would be expected for the shorter-duration intervention, these rates of opt out and pause are lower among students in the wave 2 sample. In general, the rates of opt out even among the wave 1 students are on par with opt-out rates in prior, shorter duration text-based interventions and suggest that students are generally willing to receive university communication via text message over a more sustained period of time.

Impact of messaging to encourage student engagement with social and career-related supports

Some of the outreach through the Pounce system encouraged students to engage with non-academic supports on campus, and particularly those through career services. Additional messages encouraged students to engage in social events on campus. Because we are not able to observe outcomes associated with the messages focused on social programming, in Table 5, we focus explicitly on the question of whether outreach related to career-services programming led to changes in student participation in these opportunities. In the top panel of Table 5, we present impacts corresponding to targeted campaigns (i.e., that were directed only to a subset of students), and in the bottom panel, we present impacts corresponding to campaigns sent to all students.

For each outcome, we report the control group level of take up among those in the control group who would have been targeted for a given campaign were they assigned to the treatment condition (column 1). In columns (2) and (3), we report ITT effects of the outreach with and without baseline covariate controls. In columns (4) and (5), we report results from our IV estimation, with first-stage effects of treatment assignment on message distribution in column (4) and the instrumented effect in column (5). Finally, in column (6), we report the number of students in the sample for whom the content of the message was relevant (i.e., the size of the sample included in treatment effect estimation).

The four career-services related message campaigns that were targeted and for which we can track participation outcomes were relevant for different subsets of students.[5] The fall campaign focused on graduate and professional school was targeted to juniors and seniors only, whereas the spring campaigns encouraging participation in internship or summer part-time jobs fairs were targeted toward students in the freshman, sophomore and junior classes. Finally, one campaign encouraged students to create an online portfolio-based resume using Portfolium.[6] Outreach for this campaign was very targeted and focused just on students who had not yet created their online profile. In the fall, all treatment group students received outreach regarding a multi-purpose fair focused on majors, careers and internships, and in the spring, all treatment group students received outreach regarding career week events.

Across all of the career-related campaigns (both general and targeted), we observe little to no response to the outreach. We note first that student take up of these opportunities appears to be quite low among those in the control group. Further, the campaigns focused on these events appeared to do little to sway student participation in them. A potential exception is the all-majors, career and internship fair for which Pounce improved attendance by 1 percentage point. Although this effect is small in absolute terms, it is large in relative terms (30%), given that only 3.3 percent of control group students participated in this event. The point estimate associated with take up of the Portfolium tool is larger but imprecisely estimated.

It is possible that the career-related outreach would motivate students to take up general career services supports even if they did not participate in the specific fairs that the outreach promoted. Students may, for example, be interested to receive career-related services, but scheduling constraints may prohibit their participation in events at specific dates and times. To explore this possibility, in the final two

[5] Student participation in these types of events is tracked based on students swiping their ID cards upon entry into the event. There may be some noise in the data if students are able to enter without swiping an ID.
[6] Portfolium is an online social media platform, similar to LinkedIn, which allows users to create an online portfolio to feature their academic and workplace experience and connect with employers.

rows of Table 5, we examine impacts on the total number of career services interactions that students had as well as an indicator for whether students had any engagement with career services supports during the academic year. In neither case does it appear that the outreach shaped student take up of career-services supports.

Impact of messaging to encourage student engagement in academic supports

Another set of campaigns encouraged students to engage with supports or other activities related to academics. We report on related outcomes in Table 6. Messages in this domain that focused on activities such as participating in supplemental instruction for students who were struggling academically; maintaining satisfactory academic progress (SAP); or managing the receipt of a SAP warning. Global outreach in this domain encouraged students to meet with their academic advisor. The impact of outreach focused on supplemental supports is more mixed. The outreach appeared to have no influence on students taking up supplemental instruction opportunities. In contrast, students receiving outreach about SAP were somewhat more likely to attend meetings about their academic progress. In the fall, Pounce outreach improved meeting attendance by nearly 1 percentage point, and in the spring, outreach improved meeting attendance by 2.6 percentage points, but this second result is imprecisely estimated.[7] Finally, outreach that encouraged students to meet with their academic advisor led to a 2 percentage point improvement in advisor meetings that occurred within one week of the outreach (over a control group rate of 7 percent, a nearly 29 percent improvement). However, this effect dissipated over time, such that treatment and control students were just as likely to have met with their advisor within the one-month timeframe after the outreach campaign.

[7] Note that in the spring semester compared to the fall, half the number of students received outreach regarding SAP.

Impact of messaging to encourage student completion of required administrative tasks

A final set of messages focused on administrative procedures that students needed to navigate in order to continue in good standing at GSU. Outreach to all students focused on tasks that were necessary but not entirely time sensitive (such as refiling the FAFSA and registering for the fall 2019 semester, both tasks that could be completed at some point in a several month period). Targeted outreach focused on tasks that were, for the most part, highly acute. These are tasks, such as managing an outstanding tuition bill balance or other administrative registration holds, that create immediate consequences for students if they are not resolved. We present results associated with targeted outreach in Table 7 and with outreach to all students in Table 8.

Results across these two tables point strongly to the notion that the text-based outreach is successful when it pertains to discrete, well-defined administrative processes. This is particularly so when the outreach is targeted to those students for whom it is relevant and when it is related to issues where the consequences of inaction are immediate and clear. Table 7 reports the impacts of targeted outreach to raise students' awareness of outstanding balances on term bills and / or other registration holds. During the fall semester, outreach to students with an outstanding balance on their term bill increased by 9 percentage points the share of students who resolved their balance (over a control group rate of 22 percent). Correspondingly, it cut in half the share of students who had to withdraw from GSU in that semester because of the outstanding balance. We observe effects of a similar magnitude for all other administrative tasks presented in Table 7, with the exception of attending the commencement fair.[8] The difference with this outcome is that it is not required of those expected to graduate.

[8] The fifth outcome in Table 7 pertains to the Academic Improvement Plan (AIP) hold. The AIP holds are managed by the GSU advising office. Students receive an AIP hold when they exhibit poor academic performance the semester prior. This is an overarching designation for students who receive a warning or are placed under supervision or probation for their academic performance. If a student receives an AIP hold, he must meet with his academic advisor prior to registration to formulate and agree upon academic plans for the new semester. Once this advisory step is completed, the AIP hold is considered resolved and the student is permitted to register. In contrast, the fall

In Table 8, we present results pertaining to FAFSA filing and registration for the Fall 2019 semester, topics for which all students were targeted for outreach. Although these tasks are less time sensitive (at least when related outreach began), they are still administrative procedures that are required for continuation at the university. By the end of the spring semester, students for whom the text outreach was intended were approximately four percentage points more likely to have filed the FAFSA, representing about a 6 percent improvement over the control group rate. Similarly, by the end of the spring semester, treatment group students were 3.2 percentage points more likely to be registered to continue as students in Fall 2019, relative to their control counterparts. We continued to track this outcome through the summer and found that although the treatment effect attenuated somewhat, treatment group students remained 2.2 percentage points more likely to be registered by mid-summer. These effects are consistent across the wave 1 and wave 2 samples. At the time of the mid-summer results, the university judged that it was no longer in a state of equipoise regarding whether it was valuable to extend chatbot communication to all students, particularly for raising student awareness regarding required administrative processes. In other words, after this July 22 assessment of impact on fall registration, GSU felt that it was ethically problematic to deny the tool to any undergraduates, and they expanded its use to the whole undergraduate population for outreach.

Summative outcomes

Finally, in Table 9, we present impacts for the samples overall on a set of summative outcomes including fall and spring GPA and credits earned as well as a measure for whether students graduated by the end of the Spring 2019 semester. We see a modest increase in fall 2018 GPA, but otherwise no consistent pattern of impact. Given that the outreach was particularly beneficial in helping very targeted sets of students navigating required administrative tasks and no outreach dealt directly with students'

---

registration holds (Table 7, outcome 3) include holds related to a variety of factors. These include holds related to advising and missing immunization documentation, for example.

core academic responsibilities, it is not necessarily surprising that the text outreach, as implemented, did not translate to improvement in overall academic metrics such as those we consider here.

DISCUSSION AND CONCLUSION

In this study, we experimentally assess the implementation and impact of Georgia State University's effort to use an AI-enabled chatbot to provide outreach and support to a selected set of undergraduates during the 2018-19 academic year. Our results point strongly to the conclusion that the text-based outreach was most effective at influencing student behavior when its topical focus was on discrete, well-defined administrative tasks for which the consequences of inaction were high. These are tasks like managing an unpaid portion of a tuition bill or resolving registration holds which, if unresolved, would result in a student being required to withdraw. In contrast, but paralleling Oreopoulos and Petronijevic (2019), students appeared less responsive to outreach that sought to encourage tasks related to their academics or future job prospects, for example, where the immediate consequences of inaction were likely less obvious.

Studies focused on text-based nudging in educational contexts have reached a level of maturity where we can begin to hypothesize about which characteristics of nudges are likely effective in shaping the behavior of late-adolescent and / or young adult students. Note that the context of outreach to this group is likely to differ from, for example, that of outreach to parents regarding activities with their preschool (e.g., Doss, Fahle, Loeb & York, 2019; York, Loeb & Doss, 2019) or school-aged (e.g., Kraft & Dougherty, 2013) children. Whereas parents of young children likely are able to be more future oriented, traditionally college-aged students may succumb comparatively more to limited attention, present bias and the challenge of navigating complex and competing demands.

For this group of students, text-based nudging may be particularly effective when focused on required tasks and processes that carry with them a sense of urgency and for which the consequences of inaction are immediate and tangible. Within the studies that use text-based nudging to support students in the transition from high school to college, the focal college-transition tasks (e.g., FAFSA completion and verification, placement testing, vaccinations, tuition payment, etc.) can be characterized in this way (Castleman & Page, 2015; 2017; Page & Gehlbach, 2017). Thus, text-based nudges may be best for encouraging discrete, high-stakes actions or else may need to more explicitly communicate to students about the consequences of inaction. For example, messaging about career services supports or supplemental instruction might be more effective the more they are explicit about what students stand to gain or what they are missing in the short run by not attending or participating.

Targeting and personalization of outreach may also be a key to improved effectiveness. As text-based outreach becomes more common, we should worry about saturation. That is, as students become increasingly inundated with messages, they may pay less attention, the potency of individual messages might get diluted, or students may opt out entirely. If outreach is generic and not well tailored to a given student’s particular needs, these risks may increase. One strategy for personalizing outreach is to integrate communication systems with the institution’s student information system. By incorporating student data into proactive messaging efforts, institutions can increase message relevance and credibility, target messaging appropriately to students when needed, and provide students with more specific guidance on the steps that they need to take to move forward successfully. Such targeting has been used successfully in this effort as well as prior efforts focused on FAFSA filing (Page, Castleman & Meyer, 2019) and summer melt (Page & Gehlbach, 2017) as well as in targeting outreach to students in the context of more comprehensive student success programs (e.g., Page, Kehoe, Castleman & Sahadewo, 2019).

Nevertheless, in a university setting, using a text-based platform such as Pounce involves centralizing communication and, therefore, could require substantially more and different data sharing procedures across university administrative offices absent a robust, centralized student information system. Such data sharing routines and procedures are an important foundation to the successful implementation of a chatbot tool that is reliant on student-level data (Nurshatayeva et al, 2020).

Another point to consider is students' receptivity to receiving outreach from the ostensible sender of the messages. In the intervention we consider here, outreach was framed as coming from Pounce, a friendly embodiment of the university central administration. For treatment group students in the first wave of randomization (e.g., those targeted for outreach throughout the entire 2018-19 academic year), approximately 5 percent opted out and another 8 percent paused the outreach at some point during the year. Opt out and pause rates were lower for students in the wave 2 randomization who received outreach over a shorter duration of time. Such opt out (and pause) rates are in line with prior text-based interventions where the outreach was coming from a trusted source and one from which students would expect to hear, given the topical focus of the messaging. In contrast, opt out rates tend to be higher when the outreach is delivered from a less-well-known source or one with which the student may not expect to communicate via text message (e.g., Avery et al, 2020; Page et al, 2019). In this regard, a key takeaway is that the ostensible sender of the messages matter, with students likely to be more receptive to outreach and communication from organizations and / or individuals with which they are affiliated (e.g., Debnam, 2017). The present study is consistent with this observation. In addition, if text-based communication is one component of a broader student communication strategy, it can be used to reinforce communication that students are receiving through other channels, rather than standing alone.

Relatedly, it is also worth noting that the outreach was not integrated into students' core academic experiences. That is, it did not directly relate to the curricula and assigned work in their courses. Where outreach did engage with academics, it pertained to supplemental curricular opportunities for students who were struggling academically and to administrative procedures for students who were failing to meet Satisfactory Academic Progress. Outreach on such topics has the potential to feel stigmatizing to students and, if sent separately, may feel detached from students' experiences in the classroom with their course faculty and peers. An open question is whether such nudging could be fruitfully integrated with students' core academic experiences and whether and how faculty would need to be involved. The lack of impact that we observe on academic actions (e.g., participation in supplemental instruction) and outcomes (e.g., GPA and credit attainment) aligns with recent findings from Oreopoulos and Petronijevic (2019). However, in neither their study nor this one were course faculty ostensibly involved with the communication to students. Perhaps if nudges were framed as coming from course faculty or thoughtfully aligned with important course milestones (e.g., Carrell & Kurlaender, 2020; Balaban & Conway, 2020; Smith et al, 2018), the outreach would have more potential for influencing students' academic engagement and performance.

In the effort that we investigate here, we find that centralized, text-based outreach to students regarding required (and, often, time sensitive) administrative tasks was highly effective for improving students' attention to and success with navigating administrative barriers to their ongoing progress. Across this and other studies, impacts on the order of magnitude that we observe on administrative processes can be considered impressive, given their low cost. At the same time, we recognize that these impacts are often still modest in absolute terms. Therefore, we encourage consideration of how nudges, such as those we study, can be incorporated into multi-pronged systems of support. Such systems are likely to be most successful when they account for the several dimensions – financial, academic, social, administrative, along which students can falter on the path to college success.

WORKS CITED

Avery, C., Castleman, B. L., Hurwitz, M., Long, B. T. & Page, L. C. (2020). Digital messaging to improve college enrollment and success. Working paper.

Balaban, R., & Conway, P. (2020, May). A Test of Enhancing Learning in Economics through Nudges. In *AEA Papers and Proceedings* (Vol. 110, pp. 289-93).

Bettinger, E. P., Long, B. T., Oreopoulos, P., & Sanbonmatsu, L. (2012). The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment. *The Quarterly Journal of Economics*, *127*(3), 1205-1242.

Bird, K. A., Castleman, B. L., Denning, J. T., Goodman, J., Lamberton, C., & Rosinger, K. O. (2019). *Nudging at scale: Experimental evidence from FAFSA completion campaigns* (No. w26158). National Bureau of Economic Research.

Bound, J., Lovenheim, M. F., & Turner, S. (2010). Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics*, *2*(3), 129-57.

Carrell, S. E. & Kurlaender, M. (2020). My professor cares: Experimental evidence on the role of faculty engagement (No. w27312). National Bureau of Economic Research.

Castleman, B. L., & Page, L. C. (2015). Summer nudging: Can personalized text messages and peer mentor outreach increase college going among low-income high school graduates? *Journal of Economic Behavior & Organization*, *115*, 144-160.

Castleman, B. L., & Page, L. C. (2016). Freshman year financial aid nudges: An experiment to increase FAFSA renewal and college persistence. *Journal of Human Resources*, *51*(2), 389-415.

Castleman, B. L., & Page, L. C. (2017). Parental influences on postsecondary decision making: Evidence from a text messaging experiment. *Educational Evaluation and Policy Analysis*, *39*(2), 361-377.

Castleman, B. L., Page, L. C., & Schooley, K. (2014). The forgotten summer: Does the offer of college counseling after high school mitigate summer melt among college-intending, low-income high school graduates? *Journal of Policy Analysis and Management*, *33*(2), 320-344.

Clotfelter, C. T., Hemelt, S. W., & Ladd, H. F. (2018). Multifaceted aid for low-income students and college outcomes: Evidence from North Carolina. *Economic Inquiry*, *56*(1), 278-303.

Debnam, J. (2017). Peers and persuasion across collegiate social networks. Working paper.

Doss, C., Fahle, E. M., Loeb, S., & York, B. N. (2019). More Than Just a Nudge Supporting Kindergarten Parents with Differentiated and Personalized Text Messages. *Journal of Human Resources*, *54*(3), 567-603.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The homecoming of American college women: The reversal of the college gender gap. *Journal of Economic perspectives*, *20*(4), 133-156.

Hurwitz, M., Smith, J., Niu, S., & Howell, J. (2015). The Maine question: How is 4-year college enrollment affected by mandatory college entrance exams? *Educational Evaluation and Policy Analysis*, *37*(1), 138-159.

Hyman, J. (2017). ACT for all: The effect of mandatory college entrance exams on postsecondary attainment and choice. *Education Finance and Policy*, *12*(3), 281-311.

Kena, G., Aud, S., Johnson, F., Wang, X., Zhang, J., Rathbun, A., ... & Kristapovich, P. (2014). The Condition of Education 2014. NCES 2014-083. *National Center for Education Statistics*.

Kraft, M. A., & Dougherty, S. M. (2013). The effect of teacher–family communication on student engagement: Evidence from a randomized field experiment. *Journal of Research on Educational Effectiveness*, *6*(3), 199-222.

Nurshatayeva, A., Page, L. C., White, C. C., & Gehlbach, H. (2020). Proactive student support using artificially intelligent conversational chatbots: The importance of targeting the technology. Working paper.

Oreopoulos, P., & Petronijevic, U. (2019). *The remarkable unresponsiveness of college students to nudging and what we can learn from it* (No. w26059). National Bureau of Economic Research.

Page, L. C., Castleman, B. L., & Meyer, K. (2020). Customized nudging to improve FAFSA completion and income verification. *Educational Evaluation and Policy Analysis*, *42*(1), 3-21.

Page, L. C., & Gehlbach, H. (2017). How an artificially intelligent virtual assistant helps students navigate the road to college. *AERA Open*, *3*(4).

Page, L. C., Kehoe, S. S., Castleman, B. L., & Sahadewo, G. A. (2019). More than Dollars for Scholars: The Impact of the Dell Scholars Program on College Access, Persistence, and Degree Attainment. *Journal of Human Resources*, *54*(3), 683-725.

Page, L. C., Sacerdote, B., Goldrick-Rab, S. & Castleman, B. (2019). Financial aid nudges: A national experiment with informational interventions. The Hope Center for College, Community, and Justice, Working Paper No. 3.

Page, L. C., & Scott-Clayton, J. (2016). Improving college access in the United States: Barriers and policy responses. *Economics of Education Review*, *51*, 4-22.

Smith, B. O., White, D. R., Kuzyk, P. C., & Tierney, J. E. (2018). Improved grade outcomes with an e-mailed “grade nudge”. *The Journal of Economic Education*, *49*(1), 1-7.

Weiss, M. J., Ratledge, A., Sommo, C., & Gupta, H. (2019). supporting community college students from start to degree completion: Long-term evidence from a randomized trial of CUNY's ASAP. *American Economic Journal: Applied Economics*, *11*(3), 253-97.

York, B. N., Loeb, S., & Doss, C. (2019). One step at a time the effects of an early literacy text-messaging program for parents of preschoolers. *Journal of Human Resources*, *54*(3), 537-566.

TABLES AND FIGURES

Table 1. Schedule of Fall 2018 Text Campaigns

Date	Message topic	Domain	Target	Outcome(s)
October 2	Launch Message	General	All students	No measureable outcome expected
October 2	All Majors Career & Internship Fair 2018	Non-academic supplemental	All students	Fair attendance
October 4	Outstanding balance on student bill	Administrative	Students with balance of $258 or more as of 10/4	Open case with Financial Services within 1 week; withdraw as of 10/12 (withdrawal deadline)
October 5	Withdrawal deadline	General	All students	No measureable outcome expected
October 9	Midterm time	General	All students	No measureable outcome expected
October 11	Supplemental Instruction Campaign	Academic supplemental	All students enrolled in supplemental instruction course(s)	Attendance in supplemental instruction; course/term GPA
October 16	FAFSA filing	Administrative	Students who filed 2018-2019 FAFSA	FAFSA filing
October 18	Career Services intro campaign	Non-academic supplemental	All students	Aggregate use of career services
October 18	Registration hold campaign	Administrative	Students with administrative hold(s) on registration as of 10/16	Hold resolution
October 22	Registration for spring semester (seniors only)	Administrative	All seniors who are not planning to graduate in Spring	Spring registration
October 24	Graduate and professional school fair campaign	Non-academic supplemental	Juniors and seniors	Fair attendance

Date	Message topic	Domain	Target	Outcome(s)
October 25	Maintaining SAP information session	Academic supplemental	Students at risk of not meeting SAP and losing financial aid in next semester	SAP information session attendance
October 26	Registration for spring semester (non-seniors)	Administrative	All non-senior students	Spring registration
November 1	Nudge: financial literacy (freshman)	Non-academic supplemental	All freshmen	No measureable outcome expected
November 1	Financial Literacy (seniors)	Non-academic supplemental	All seniors	No measureable outcome expected
November 1	Financial Literacy (transfer/transition)	Non-academic supplemental	Fall 2018 new transfer and transition students	No measureable outcome expected
November 2	Nudge: meet with your advisor (Fall 2018)	Academic supplemental	All students	Meeting with academic advisor (whether / when)
November 5; December 5	Registration for spring semester	Administrative	Students not yet registered for Spring	Spring registration
November 6	International Education Week	Non-academic supplemental	All students	No measureable outcome expected
November 8	International Thanksgiving Feast	Non-academic supplemental	International students	No outcome (target N too small)
November 14	Spring financial aid award	Administrative	All students	No measureable outcome expected
November 15	Portfolium	Non-academic supplemental	Students who had not created a Portfolium account	Creation of Portfolium account
November 19	Fall break	General	All students	No measureable outcome expected
December 3	Last day of classes	General	All students	No measureable outcome expected
December 11	End of term, grade reporting	General	All students	No measureable outcome expected

Table 2. Schedule of Spring 2019 Text Campaigns

Date	Message topic	Domain	Target	Outcome
January 7, 17	Spring 2019 registration – Students with/without holds	Administrative	Students who have not yet registered for Spring	Spring registration
January 7, 22	Spring 2019 registration – balance reduction	Administrative	Students who have registered but have remaining balances on their accounts	Resolution of student balance
January 14	First day back: Spring 2019	General	All students	No measureable outcome expected
January 20	MLK Day	General	All students	No measureable outcome expected
January 21; February 28	Internship & Co-Op Fair	Non-academic supplemental	Sophomores and juniors	Event registration and attendance
February 7 (& monthly)	FAFSA filing	Administrative	All students; messages targeted over time to subset not filed	FAFSA filing (whether / when)
February 8, 13	AIP hold (warning, supervision, probation)	Administrative	Students with an AIP-related hold	Hold resolution
February 11, 20	Financial aid award flag	Administrative	Students with flags that would prevent them from receiving financial aid for Spring term and are at risk of being withdrawn for non-payment	Flag resolution
February 14	Study abroad	General	All students	No measureable outcome expected
February 18, 25	Career Week	Non-academic supplemental	All students	Event registration and attendance
February 26; April 23	Registration for summer semester	Administrative	All continuing students	Registration outcome

Date	Message topic	Domain	Target	Outcome
March 4	UAC Mini Major Fair	Academic supplemental	Students with undeclared major	No outcome (target N too small)
March 5	Withdrawal deadline	General	All students	No measureable outcome expected
March 8, 19	ISSS & ISAC Cross-Cultural Trip	Non-academic supplemental	International students and students who have participated in Summer 2018 study abroad program	No measureable outcome expected
March 12	Spring 2019 launch	General	Wave 2 students	No measureable outcome expected
March 14	Spring break/Study Abroad IG link	General	All students	No measureable outcome expected
March 25	Commencement fair	Non-academic supplemental	Degree candidates for Spring 2019 graduation	Fair attendance and graduation outcome
March 26 (& monthly)	Fall 2019 registration	Administrative	All continuing students. Messages targeted over time to subset not registered	Registration outcome
April 1	International Spring Festival	Non-academic supplemental	International students	No measureable outcome expected
April 2, 5, 16	Registration hold resolution	Administrative	Students with one or more administrative holds on registration	Hold resolution
April 10	SAP (Satisfactory Academic Progress) warning	Academic supplemental	Students at risk of not meeting SAP and losing financial aid in next semester	Open case with Financial Services
April 15	Summer Part-Time Job Fair	Non-academic supplemental	All students who are not graduating seniors	Event registration and attendance
April 29	Final exams	General	All students	No measureable outcome expected
May 2	Commencement	General	Degree candidates for Spring 2019 graduation	Degree award status
May 10	Grade posting	General	All students	No measureable outcome expected

Table 3. Descriptive statistics by wave of randomization and treatment status

	Wave 1 sample		Wave 2 sample	
	Control (N = 3,856)	Treatment (N = 3,724)	Control (N = 3,037)	Treatment (N = 3,039)
Freshman	0.53	0.52	0.10	0.10
Sophomore	0.27	0.27	0.19	0.19
Junior	0.07	0.06	0.41	0.41
Senior	0.13	0.14	0.30	0.30
Hispanic	0.14	0.13	0.12	0.12
White	0.30	0.29	0.29	0.30
Black	0.42	0.43	0.47	0.46
Asian	0.16	0.17	0.12	0.13
Multi-racial	0.09	0.08	0.08	0.08
First-generation college goer	0.24	0.24	0.27	0.25
Female	0.59	0.59	0.62	0.61
Filed FAFSA	0.93	0.93	0.88	0.89
Received financial aid	0.86	0.87	0.81	0.82
Received Pell grant	0.48	0.47	0.49	0.51
Grant amount ($)	1240	1204	1187	1223
	(1391)	(1388)	(1333)	(1353)
Loan amount ($)	1911	2007	2551	2452
	(2856)	(3000)	(3125)	(2998)
Age (years)	20.24	20.26	23.48	23.45
	(5.34)	(5.21)	(6.97)	(6.81)
Credit hours earned	35.42	35.83	76.58	75.96
	(40.29)	(41.64)	(37.30)	(36.58)
GSU GPA	3.16	3.17	2.96	2.96
	(0.62)	(0.61)	(0.82)	(0.82)

Source: GSU administrative records.
Notes: Each cell reports sample average. For continuous measures, standard deviation reported in parentheses. Statistically significant differences in baseline characteristics assessed by regressing each baseline characteristic on an indicator of treatment assignment and fixed effects for group within which randomization was conducted. We observe balance on all baseline measures when assessed for the waves separately and for the data pooled across waves.

Table 4. Chatbot engagement and opt-out

Outcome	Total N	Control mean	Wave 1 ITT	Wave 2 ITT
N outgoing messages	244,673	0.00	56.721*** (0.345)	10.950*** (0.088)
N outgoing campaign messages	233,265	0.00	54.243*** (0.332)	10.240*** (0.077)
N outgoing auto-response messages	5,554	0.00	1.133*** (0.050)	0.434*** (0.029)
N outgoing staff response messages	16	0.00	0.004*** (0.001)	0.001 (0.000)
N outgoing triage messages	777	0.00	0.136*** (0.008)	0.089*** (0.007)
N incoming messages	15,980	0.00	3.323*** (0.077)	1.178*** (0.040)
N incoming survey response messages	9,056	0.00	1.894*** (0.041)	0.656*** (0.018)
N incoming question	5,555	0.00	1.134*** (0.050)	0.434*** (0.029)
N incoming messages escalated to staff member	42	0.00	0.010*** (0.002)	0.002** (0.001)
Opt out		0.00	0.048*** (0.004)	0.011*** (0.002)
Pause participation		0.00	0.080*** (0.004)	0.048*** (0.004)
N			7,580	6,076

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports results from fitting equation (1) to outcome data for outcomes reported in first column. No covariates were included in modeling these outcomes. Robust standard errors in parentheses.

Table 5. Experimental effects of text-based outreach on take up of career-related supports

Term	Campaign topic	Outcome	Control mean	ITT effect	ITT effect	First-stage	IV effect	N
			Outreach to targeted subset					
Fall	Graduate and Professional School Fair Campaign	Attend fair	0.012 (0.004)	-0.004 (0.005)	-0.004 (0.005)	0.892*** (0.011)	-0.004 (0.006)	1,517
Fall	ePortfolio tool	Create ePortfolio profile	0.942 (0.020)	0.026 (0.026)	0.041 (0.029)	0.838*** (0.033)	0.050 (0.033)	245
Spring	Internship & Co-Op Fair	Attend fair	0.017 (0.002)	0.002 (0.003)	0.002 (0.003)	0.861*** (0.006)	0.002 (0.004)	6,652
Spring	Summer Part-Time Job Fair	Attend fair	0.008 (0.001)	0.003 (0.002)	0.003 (0.002)	0.862*** (0.005)	0.003 (0.002)	10,207
			Outreach to full sample					
Fall	All Majors Career & Internship Fair 2018	Attend fair	0.033 (0.003)	0.010** (0.004)	0.010** (0.004)	0.935*** (0.004)	0.010** (0.005)	7,580
Spring	Career Week Spring 2019	Attend career week event	0.010 (0.002)	-0.000 (0.002)	-0.000 (0.002)	0.769*** (0.007)	-0.000 (0.003)	7,580
Both		Total number of career services interactions	0.234 (0.009)	0.011 (0.012)	0.011 (0.012)	0.821*** (0.004)	0.013 (0.015)	13,656
Both		Any career services interactions	0.146 (0.004)	0.009 (0.006)	0.008 (0.006)	0.821*** (0.004)	0.010 (0.007)	13,656
		Covariates			X	X	X	

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports on a series of regression models to assess the impact of chatbot outreach on a given outcome. Each row reports the topical focus of the campaign as well as the specific outcome assessed. Results columns 1 and 2 report the control average outcome and ITT effect from a regression that includes only fixed effects for groups within which randomization was conducted. Column 3 reports covariate controlled ITT effects from a model including all covariates listed in Table 1. Column 4 reports the first-stage effect of assigning a student for outreach on actual message distribution. Column 5 reports the IV-adjusted effect of message distribution on the outcome of interest. Robust standard errors in parentheses.

Table 6. Experimental effects of text-based outreach on take up of academic supports

Term	Campaign topic	Outcome	Control mean	ITT effect	ITT effect	First-stage	IV effect	N
		Outreach to targeted subset						
Fall	Supplemental Instruction Campaign	Attend supplemental instruction	0.256 (0.012)	-0.008 (0.017)	-0.000 (0.014)	0.941*** (0.007)	-0.000 (0.015)	2,659
Fall	Maintaining Satisfactory Academic Progress	Attend SAP meeting	0.000 (0.000)	0.007** (0.004)	0.008** (0.004)	0.922*** (0.012)	0.008** (0.004)	1,085
Spring	Maintaining Satisfactory Academic Progress	Attend SAP meeting	0.049 (0.014)	0.026 (0.022)	0.021 (0.021)	0.853*** (0.023)	0.025 (0.024)	515
		Outreach to full sample						
Fall	Nudge: Meet with your advisor (Fall 2018)	Meet with advisor within 1 week	0.071 (0.004)	0.019*** (0.006)	0.020*** (0.006)	0.914*** (0.005)	0.021*** (0.007)	7,580
		Meet with advisor within 2 weeks	0.123 (0.005)	0.011 (0.008)	0.012 (0.008)	0.914*** (0.005)	0.013 (0.008)	7,580
		Meet with advisor within 1 month	0.166 (0.006)	0.001 (0.008)	-0.010 (0.009)	0.914*** (0.005)	-0.011 (0.010)	7,580
		Covariates			X	X	X	

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports on a series of regression models to assess the impact of chatbot outreach on a given outcome. Each row reports the topical focus of the campaign as well as the specific outcome assessed. Results columns 1 and 2 report the control average outcome and ITT effect from a regression that includes only fixed effects for groups within which randomization was conducted. Column 3 reports covariate controlled ITT effects from a model including all covariates listed in Table 1. Column 4 reports the first-stage effect of assigning a student for outreach on actual message distribution. Column 5 reports the IV-adjusted effect of message distribution on the outcome of interest. Robust standard errors in parentheses.

Table 7. Experimental effects of targeted text-based outreach on completion of administrative processes

			(1)	(2)	(3)	(4)	(5)	(6)
Term	Campaign topic	Outcome	Control mean	ITT effect	ITT effect	First-stage	IV effect	N
			Outreach to targeted sample					
Fall	Outstanding balance on fall term bill	Resolve balance	0.224	0.090**	0.077*	0.969***	0.080*	374
			(0.029)	(0.045)	(0.046)	(0.013)	(0.046)	
		Withdraw for semester	0.209	-0.101***	-0.103***	0.969***	-0.107***	374
			(0.028)	(0.036)	(0.036)	(0.013)	(0.036)	
Fall	Registration hold(s)	Resolve hold(s)	0.370	0.081***	0.074***	0.994***	0.074***	1,670
			(0.016)	(0.023)	(0.023)	(0.003)	(0.023)	
Spring	Outstanding balance on spring term bill	Resolve balance	0.728	0.087	0.099*	0.842***	0.118*	257
			(0.040)	(0.055)	(0.054)	(0.034)	(0.061)	
Spring	Academic Improvement Plan hold	Resolve hold	0.230	0.074*	0.070*	0.871***	0.081*	529
			(0.026)	(0.039)	(0.039)	(0.021)	(0.044)	
Spring	Financial Aid Award hold	Resolve hold	0.229	0.060	0.059	0.881***	0.067	438
			(0.028)	(0.042)	(0.042)	(0.022)	(0.047)	
Spring	Commencement Fair	Attend fair	0.869	0.009	-0.007	0.847***	-0.008	317
			(0.027)	(0.037)	(0.037)	(0.028)	(0.041)	
		Covariates			X	X	X	

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports on a series of regression models to assess the impact of chatbot outreach on a given outcome. Each row reports the topical focus of the campaign as well as the specific outcome assessed. Results columns 1 and 2 report the control average outcome and ITT effect from a regression that includes only fixed effects for groups within which randomization was conducted. Column 3 reports covariate controlled ITT effects from a model including all covariates listed in Table 1. Column 4 reports the first-stage effect of assigning a student for outreach on actual message distribution. Column 5 reports the IV-adjusted effect of message distribution on the outcome of interest. Robust standard errors in parentheses.

Table 8. Experimental effects of text-based outreach on completion of administrative processes

			(1)	(2)	(3)	(4)	(5)	(6)
Term	Campaign topic	Outcome	Control mean	ITT effect	ITT effect	First-stage	IV effect	N
			Outreach to full sample					
Spring	2019-2020 FAFSA reminder (sent monthly)	Filed FAFSA by March 14	0.405 (0.006)	0.009 (0.008)	0.007 (0.008)	0.728*** (0.005)	0.009 (0.011)	13,656
		Filed FAFSA by April 18	0.552 (0.006)	0.037*** (0.008)	0.033*** (0.008)	0.731*** (0.005)	0.045*** (0.011)	13,656
		Filed FAFSA by end of spring semester	0.590 (0.006)	0.037*** (0.008)	0.033*** (0.008)	0.731*** (0.005)	0.045*** (0.010)	13,656
Spring	Fall 2019 registration (sent monthly)	Registered for fall by April 16	0.494 (0.006)	0.046*** (0.008)	0.043*** (0.008)	0.821*** (0.005)	0.053*** (0.010)	13,656
		Registered for fall by May 22	0.631 (0.006)	0.032*** (0.008)	0.029*** (0.008)	0.821*** (0.005)	0.036*** (0.009)	13,656
		Registered for fall by June 24	0.659 (0.005)	0.028*** (0.008)	0.025*** (0.008)	0.821*** (0.005)	0.030*** (0.009)	13,656
		Registered for fall by July 22	0.697 (0.005)	0.022*** (0.007)	0.020*** (0.007)	0.821*** (0.005)	0.024*** (0.009)	13,656
		Covariates			X	X	X	

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports on a series of regression models to assess the impact of chatbot outreach on a given outcome. Each row reports the topical focus of the campaign as well as the specific outcome assessed. Results columns 1 and 2 report the control average outcome and ITT effect from a regression that includes only fixed effects for groups within which randomization was conducted. Column 3 reports covariate controlled ITT effects from a model including all covariates listed in Table 1. Column 4 reports the first-stage effect of assigning a student for outreach on actual message distribution. Column 5 reports the IV-adjusted effect of message distribution on the outcome of interest. Robust standard errors in parentheses.

Table 9. Experimental effects of text-based outreach on overall outcomes

		(1)	(2)	(3)	(4)
Term	Outcome	Control mean	ITT effect	ITT effect	N
Fall	Fall 2018 credit hours earned	48.596 (0.285)	0.104 (0.425)	-0.005 (0.150)	7,580
Fall	Fall 2018 term GPA	2.900 (0.017)	0.107*** (0.024)	0.098*** (0.022)	7,580
Spring	Spring 2019 credit hours earned	71.873 (0.222)	-0.093 (0.322)	0.071 (0.139)	13,656
Spring	Spring 2019 Term GPA	2.712 (0.015)	0.001 (0.021)	-0.009 (0.020)	13,656
Spring	Graduated	0.047 (0.002)	-0.004 (0.003)	-0.004 (0.003)	13,656
	Covariates			X	

*p < 0.10 **p < 0.05 ***p<0.001

Source: GSU administrative records. Notes: Each row reports on a series of regression models to assess the impact of chatbot outreach on a given outcome. Each row reports the outcome assessed. Results in columns 1 and 2 report the control average outcome and ITT effect from a regression that includes only fixed effects for groups within which randomization was conducted. Column 3 reports covariate controlled ITT effects from a model including all covariates listed in Table 1. Robust standard errors in parentheses.