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STAYING CONNECTED:
EXPERIMENTAL EFFECTS OF COACH-DELIVERED TEXT MESSAGES
IN AN ADULT HIGH SCHOOL

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ABSTRACT

More than 23 million adults in the United States lack a high school diploma, and most who return to school drop out before graduating. We evaluate a randomized intervention of adult high school students in which coaches delivered text messages that encouraged persistence. We find that assignment to treatment increased graduation by 4.9 percentage points, and the effect of message receipt among compliers is 9.3 percentage points, a 41 percent increase relative to the control mean. The intervention operated on the intensive margin by increasing the number of courses completed, but did not affect student enrollment. The effects of the intervention are concentrated among students assigned to experienced coaches, who customized their messages more extensively. We contextualize the economic impact of the low-cost intervention by comparing labor market earnings of graduates to non-graduates, which implies an earnings benefit of \$149 per treated student over four years.

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A randomized controlled trials registry entry is available at
<https://www.socialscienceregistry.org/trials/6383>

I Introduction

More than 23 million adults in the United States do not have a high school diploma, an issue that remains relevant today as 13 percent of high school students fail to graduate on time.¹ Adults without a high school diploma work fewer hours, are more likely to live in poverty, and are less likely to have health insurance (Branch, 2023; Shrider, 2024). Young adults with a high school diploma earn nearly 80 percent more than their counterparts without a high school degree. The common path to further education for adults without a diploma includes studying for and passing a high school equivalency test like the General Educational Development (GED). Yet growing evidence suggests that the economic returns to such alternative credentials are modest or concentrated among particularly disadvantaged students (Darolia, Mueser and Cronin, 2021; Heckman, Humphries and Mader, 2011; Jepsen, Mueser and Troske, 2016; Murnane, Willett and Tyler, 2000; Tyler, Murnane and Willett, 2000; Tyler and Kling, 2007).

Recognizing the benefits of a traditional diploma over high-school-equivalency substitutes, charitable organizations, state governments, and public school corporations have sponsored programs that allow adults to return to school, where they complete any remaining credits to earn their degree. Among students who previously dropped out of high school, the private and social benefits of obtaining a high school diploma from these programs are significant (Brough, Phillips and Turner, 2024; Merola, Phillips and Turner, 2025). Yet, many of these adult enrollees face substantial socioeconomic challenges and financial burdens that place them at a heightened risk of dropping out. For example, in the Goodwill Excel Center, a collection of adult charter high schools across the United States, graduation rates remain between 20 and 25 percent (Brough, Phillips and Turner, 2024). To date there is little evidence on effective strategies for helping these students persist through completion.

In this paper, we estimate the educational and implied labor market benefits of a nudge text message intervention conducted at The Goodwill Excel Center (TEC) in Austin, Texas, which began enrolling adult high school students in 2013. Nudging—light-touch interventions in which an individual’s behavior can be influenced predictably without restricting choices or greatly altering their financial incentives—is an increasingly studied and promising tool to improve educational outcomes (Damgaard and Nielsen, 2018; Thaler and Sunstein, 2008). In The Excel Center, students pick up from their existing academic standing and, if necessary, take remedial coursework to achieve grade-level competency in key subjects like reading and math. The school supports adult learners in overcoming obstacles to graduation through an accel-

¹Descriptive information in this paragraph based on authors’ calculations using the 2015–2019 ACS (Ruggles et al., 2020) and 2024 NCES reports (National Center for Education Statistics, 2024).

erated and individualized curriculum, flexible class schedules, non-academic services, and transportation assistance. The program further integrates professional certifications and community college credits into the high school curriculum. Central to this study, the program employs life coaches to foster engagement and persistence. Life coaches at the Excel Center act as student advocates by building relationships and providing tailored resources to overcome educational barriers.

The intervention leveraged the existing relationship between students and their life coaches by randomizing which students in each coach’s caseload received targeted text messages designed to promote academic persistence. The messages asked questions to elicit student engagement with program resources, emphasized graduation requirements, and gave information about post-secondary opportunities. Messages addressed four primary areas: program completion, academic diligence, post-secondary pursuits, and fulfillment of program requirements. To maintain variety while preserving consistent content, the messaging system used a “mix-and-match” structure that combined interchangeable *hooks* and *directives*. Life coaches could rephrase messages, add pertinent details, and contribute new hooks or directives aligned with the intervention’s core content, allowing outreach to be tailored to individual students.

We evaluate the intervention using a randomized controlled trial conducted from September 2020 through February 2022 involving 895 adult students working toward a high school diploma at TEC in Austin, TX. Within life coach caseloads, 403 were assigned to a treatment group that received the text message intervention, while 492 were assigned to a control group that received business-as-usual supports. We link study participants to administrative data on enrollment and educational attainment to estimate the intervention’s effects on persistence and graduation. To quantify the potential economic value of any effect on graduation, we separately estimate the relationship between graduation and subsequent earnings among a broader sample of TEC students in Austin, controlling flexibly for two years of pre-enrollment earnings (Brough, Phillips and Turner, 2024). We then combine this estimated earnings difference with the experimental effect on graduation to calculate the intervention’s implied earnings benefits.

We find that students receiving the text message intervention were relatively more likely to graduate with a high school diploma. Assignment to the text intervention increased graduation by 4.9 percentage points. Instrumenting message receipt with assignment yields a 9.3-point effect among compliers, a 41 percent increase relative to the control group graduation rate of 22.6 percent. We find little difference in term-by-term enrollment rates. Rather, treated students were more likely to earn credits from the classes they were already enrolled in. This pattern offers suggestive evidence that the nudges operated on the

intensive margin, encouraging enrolled students to finish their coursework, rather than on the extensive margin of remaining enrolled for additional terms. Consistent with this interpretation, treated students complete more credits in core graduation subjects, with the largest gains in reading and social studies. The intervention did not crowd in or crowd out other forms of student support, as staff-recorded case notes of contact with students trend similarly across the treatment and control groups. Separate from the life coaches who delivered the intervention, the school assigns graduates an alumni coach for college and job placement. We find suggestive evidence that treated students had more contact with these coaches, consistent with more of them reaching graduation. Our main findings potentially mask heterogeneity in the graduation effect, as exploratory subgroup point estimates are larger among white students, female students, and students who had already accumulated some credits before treatment. That the effect is largest for students who entered with credits in hand provides further support for an intensive-margin response, as these students were closer to completing their diploma.

To better understand the intervention’s mechanisms, we explore the content of the nudges and the characteristics of the life coaches who sent them. Because the life coaches deliver the messages, the effect can depend on who sends them and how. We find the graduation effect is driven by life-coach experience rather than the number of nudges. Splitting students by how many nudges their coach sends in the first term after treatment assignment yields no distinguishable difference in the effect on graduation. Conversely, point estimates are larger for students assigned to experienced coaches rather than more recently hired coaches, although the difference across coach types is imprecisely estimated. Experienced coaches differ in how they use the intervention, being more likely than inexperienced coaches to send customized messages while also sending shorter texts. Rather than experienced life coaches using nudges to facilitate further conversation, either with themselves or academic advisors, we find evidence they increased engagement with TEC program resources. Proxying for engagement with student-portal logins, treatment increased logins by 3.3 logins per enrolled term (31 percent) among students assigned to experienced life coaches, whereas treated students assigned to inexperienced life coaches experienced a small, statistically insignificant decline in logins. However, we read these patterns as suggestive because the experiment was not designed with treatment arms to test these channels.

Finally, we assess the economic significance of the graduation effect by estimating the labor market returns associated with Excel Center graduation among TEC students in Texas. We link students in Austin to administrative earnings records and implement a strategy from [Brough, Phillips and Turner](#)

(2024) comparing changes in earnings before and after enrollment for graduates and students who exited before graduation. By the fourth year after enrollment, graduates earn more than \$600 per quarter more than non-graduates, and the estimated net present value of this earnings differential over the first four years is approximately \$1,600. Combining this estimate with the 9.3 percentage point experimental increase in graduation implies an earnings benefit of approximately \$149 per treated complier over the first four years.

This paper makes several contributions to the existing literature. First, we contribute to the literature on educational nudges and other light-touch interventions designed to improve student outcomes. We show that a low-cost text message intervention can promote sustained engagement and high school completion among adults who previously left high school and returned to earn a diploma. Most related studies focus on traditional-age students and target discrete decisions related to college access, such as completing financial aid applications, satisfying enrollment requirements, or matriculating after high school (Bettinger et al., 2012; Bird et al., 2021; Castleman and Page, 2015; Castleman and Long, 2016; Castleman and Page, 2016, 2017; Hastings, Neilson and Zimmerman, 2015; Hoxby and Turner, 2015; Hyman, 2020; Peter and Zambre, 2017).² Other work demonstrates that behaviorally-informed messages to parents can encourage repeated investments in children’s learning and improve students’ attendance and academic performance (Bergman, Edmond-Verley and Notario-Risk, 2018; Berlinski et al., 2025; Mayer et al., 2019; York, Loeb and Doss, 2019; Musaddiq, Prettyman and Smith, 2024). Our study instead examines light-touch outreach directed to adult students themselves, where success requires sustaining engagement over time. The closest prior study is Chande et al. (2015), which sends encouraging text messages to adults in short government-subsidized literacy and numeracy courses in the United Kingdom and finds that the messages improve early attendance in the course. We extend this evidence by studying a longer and higher-stakes outcome, completion of a high school diploma over multiple terms. Further, our messages come from the student’s own life coach rather than the research team, which lets us examine how the sender and content of a nudge shape its effect and trace the graduation effect through to earnings.

Second, we show how the delivery of educational nudges may shape their effectiveness. Recent evidence documents substantial heterogeneity in the effectiveness of behavioral interventions across nudge types and settings (List et al., 2026). We show that heterogeneity may also arise from how an intervention is delivered. Our intervention relied on life coaches who were already responsible for supporting the students in their caseloads and could tailor messages to students’ circumstances and needs. We find suggestive evidence that this relational component matters. The graduation effect is concentrated among students assigned

²See Damgaard and Nielsen (2018) and French and Oreopoulos (2017) for reviews of this literature.

to experienced life coaches who customized their messages more extensively than recently hired coaches. By contrast, effects do not vary meaningfully with the number of messages a coach sent. These patterns suggest that the effectiveness of light-touch outreach may depend less on the intensity of communication than on the experience of the sender and how the intervention is used.

Our design therefore places the intervention between conventional nudges, which are inexpensive and scalable but often impersonal, and intensive advising or case-management programs, which provide individualized support but require considerably more resources. This tradeoff is illustrated by [Oreopoulos and Petronijevic \(2018\)](#), who find that one-on-one coaching improves university students’ academic outcomes, while stand-alone text-message and online interventions do not. Other research shows that comprehensive advising, coaching, and case management can substantially increase persistence and degree completion among community college students ([Barr and Castleman, 2025](#); [Carrell and Sacerdote, 2017](#); [Evans et al., 2020](#); [Weiss et al., 2019](#)). Our intervention occupies a different point on this continuum, using a low-cost technology to extend the work of coaches who already support the students receiving the messages. In this way, the intervention combines some of the scalability of technology-based nudges with the relational support provided by individualized coaching.

Third, our findings speak to the challenge of sustaining student engagement in remote and hybrid educational environments. Prior research documents that online instruction can reduce academic performance and persistence, particularly among students who face greater barriers to remaining enrolled ([Bueno, 2020](#); [Kofoed et al., 2024](#)). Closest to our intervention, [Lichand, Christen and van Egeraat \(2023\)](#) examine text messages targeting students’ socio-emotional skills during pandemic-related school closures in Brazil and find no statistically significant average reduction in dropout risk, although they report an imprecisely estimated reduction among students with lower baseline achievement. Part of our intervention occurred while TEC relied on remote and hybrid instruction during the COVID-19 pandemic, a period when maintaining contact with adult learners was especially difficult. We complement the evidence by studying messages delivered through existing relationships with school-based coaches and by measuring effects on academic progress and high school graduation. Our findings show how low-cost, relationship-based communication can help schools support at-risk students when opportunities for in-person interaction are limited.

Finally, we contribute to the limited evidence on how to increase high school completion among adults who previously dropped out. A large literature documents substantial private and social returns to completing high school ([Angrist and Krueger, 1991](#); [Oreopoulos, 2006](#)). Emerging evidence suggests that these

benefits also extend to adult-serving high schools. Graduates earn more than comparable non-graduates (Bennett, Blundell and Salvanes, 2021; Brough, Phillips and Turner, 2024) and are less likely to become involved with the criminal justice system (Merola, Phillips and Turner, 2025). Yet many adults who return to high school still fail to complete, suggesting that substantial returns alone are not enough to overcome the barriers they face. Our findings therefore complement evidence on alternative and re-engagement schools designed either to prevent students from leaving high school or to re-enroll those who have already left (Bloom, 2010; Dynarski and Wood, 1997; Mallah, Abdul-Razzak and Bhatt, 2026). Whereas prior work largely studies access to or the overall effectiveness of these alternative pathways, we identify a low-cost strategy for increasing persistence and completion among adults already enrolled in a re-engagement high school. By combining the experimental graduation effect with estimates of the earnings gains associated with an Excel Center diploma, we also assess the intervention’s potential economic value.

The remainder of the paper proceeds as follows. Section II describes the Excel Center, the role of life coaches, and the design of the nudging intervention. We then detail the experiment, sample, and data in Section III, followed by our empirical strategy in Section IV. Section V presents the main results on enrollment and graduation. In Section VI, we explore the mechanisms behind the graduation effect. Before concluding, Section VII links graduation to administrative earnings records to quantify the labor market returns at stake. Section VIII discusses the findings and their implications for adult education policy.

II Background

II.A The Excel Center

The Excel Center (TEC) is a national network of tuition-free charter high schools for adult learners operated by Goodwill. The school model was initially created by Goodwill of Central and Southern Indiana in 2010 and has since scaled through The Excel Center network to more than 45 locations, including Austin, Texas, where this study took place. At the time of this study, Goodwill operated three public campuses across the city.³

Adults without a traditional high school degree enroll at TEC campuses via a year-round application process. Adults are eligible to enroll if they meet age (18–50), prior educational attainment (lack a high school credential), and residency requirements. After orientation, eligible applicants are allowed to enroll

³Their primary Norwood Campus serves the majority of adult learners, is located in North Austin, and offered both day and night classes. Students were additionally served in South Austin by smaller campuses offering only day classes, including one co-located with American YouthWorks (AYW).

in classes in the next available term. As a result of the COVID-19 pandemic, TEC Austin operated with a hybrid in-person/remote model during the 2020–2021 academic year (AY); classes shifted primarily to in-person during the 2021–2022 AY.

Students often enter TEC with a sufficient number of general credits that can be applied towards their degree.⁴ Enrollees continue to take credits until they earn either their Minimum or Foundation High School diploma.⁵ Apart from completing the required number of credits, students must also complete a set of end-of-course (EOC) exams, though EOC requirements have changed significantly over the course of the 2000s. During the time of this study, students were required to complete EOC exams in Algebra 1, English 1, English 2, Biology, and U.S. History.

TEC is designed to help students who dropped out of high school overcome barriers to both earning their traditional high school degree and advancing labor-market prospects. TEC intentionally differs from traditional high schools in several ways to fulfill this mission. First, course plans are designed to meet students' level of knowledge. Placement test results and existing transcripts guide what classes students should be taking. Furthermore, students often take remedial classes in English and Math, especially when there is a large gap between when they were last in an academic environment. To support students for whom English is a second language, TEC offers a yearlong ESL academy at their Norwood campus.

Second, class schedules are flexible to accommodate all adult learners, especially those with family or work obligations. Students can register for full- or half-day schedules, and classes are offered during both the day and night to allow students to work while completing their coursework. The academic year is split into five eight-week terms, so students can resume their coursework more quickly if something pulls them away from TEC for an extended period of time. The intensive term layout also can accelerate students' time to graduation.

Third, there are extensive support services targeting nonacademic barriers to graduation: on-site child care, pregnancy-related services,⁶ bus passes and gas cards to facilitate transportation, a supplemental food pantry, and complementary counseling services. TEC campuses are also near public-transit routes. Students are also paired with a life coach who helps them set goals and overcome obstacles both in and outside of the classroom.

⁴Table 1 shows that students in the experiment transfer between 5 to 6 credits to TEC on average.

⁵Texas changed the traditional high school diploma structure in AY 2015. Students who were initially enrolled in ninth grade in AY 2015 or later work towards the Foundation High School Degree, while those entering before earn the Minimum High School Degree.

⁶New mothers are allowed to enroll in special classrooms allowing them to complete coursework while also caring for their newborn, while online education is provided for during a six-week postpartum period.

Finally, TEC curriculum and resources are centered on providing access to post-secondary education and labor market opportunities. Students create a college or career path in their first term. Elective credits can be used to earn professional certifications in careers involving, for example, welding, auto repair, or nursing. Students planning to enter a career immediately following graduation can utilize job-placement assistance to find employment. Students can also earn dual-enrollment credits, putting them on the path to attending college post-graduation.⁷ TEC also partners with Capital IDEA, which provides opportunities to fund post-secondary education. All graduating students are given an alumni coach whose role is to help facilitate challenges with entering either the labor market or college.

Evidence from TEC in Indiana shows that graduates are more likely to be employed in higher-earning jobs, as they experience sizable gains in labor market earnings—roughly \$900 per quarter five years after application (Brough, Phillips and Turner, 2024) relative to non-enrolling applicants. This equates to over an \$80,000 increase in the net present value of lifetime earnings. Furthermore, graduates of the Excel Center are also less likely to interact with the criminal justice system compared to similarly at-risk Excel Center applicants who did not graduate (Merola, Phillips and Turner, 2025).

Despite the varied supports provided to students and the large economic returns experienced by graduates, graduation rates remain low. Across Excel Center campuses in Indiana from 2013–2015, roughly 20–25 percent of students completed their diploma (Brough, Phillips and Turner, 2024). Many students leave because of conflicts with work, disinterest in the material, or issues in their personal or family life that make it challenging to commit to consistent classroom education.⁸ Similarly, low graduation rates in the Austin, TX campuses motivate the current study.

II.B Life Coaches and Nudges

Life coaches play a crucial role at TEC, serving as student engagement advocates and facilitators.⁹ They oversee groups of fifty to eighty students, fostering individual relationships to identify and address obstacles—both academic and non-academic—that may hinder educational progress. Explicit responsibilities include managing and monitoring student information, developing each student’s overall class schedule each term, collaborating with instructional staff on educational plans, and connecting students

⁷These dual-enrollment courses are predominantly offered by Austin Community College.

⁸Students are automatically unenrolled in TEC if they are absent for ten consecutive class days without any prior communication or notice.

⁹Students are generally assigned to life coaches on a capacity basis. Exceptions are often made to match students to specific life coaches when a student’s native language is Spanish or other special cases arises. Life coaches can and often do serve students at multiple campuses. Students are guaranteed a life coach, and are typically mentored by the same life coach while enrolled in TEC. If a life coach leaves TEC, a student will be given another coach in their stead.

with supportive resources. They also assist alumni in transitioning to further education or viable career opportunities. By guiding students through problem-solving processes, coaches help them stay on track toward earning their diplomas and pursuing future education and career paths.

As a way of more consistently communicating with students and promoting engagement, the Excel Centers in Austin, TX piloted a nudging intervention that aimed to improve persistence and graduation. The goal was to provide consistent and frequent communication with students and provide a message that caught students' attention and prompted them to act. Life coaches were instructed to send weekly texts to students with a two-part message that included a hook to draw attention and a direction that prompted a tangible step that contributed towards their educational or career goals.

To assist life coaches with this task, program staff developed a bank of suggested hooks and directions that could be created in a “mix and match” format. Message content fell into one of four categories: (i) messages about completing the program; (ii) messages about work throughout the term; (iii) messages about post-secondary school; (iv) messages about staying on top of requirements. For example, if the end of the term was approaching, the coach might send the following:

“Only 3 weeks left in the term! [hook] Take a minute to remember the goals that you created for yourself. You can power through! [direction]”

This message, which fits into the “work throughout the term” category, provides a small nudge to re-center the student's thoughts on their “why” at a time in the term when encouragement might be needed. For students nearing completion, coaches might send a message related to their educational path following graduation:

“Hi Denise, a lot of students at the Excel Center want to go to college after they graduate. [hook] Would you be interested in discussing this sometime? In the meantime, here's a list of programs near here: LINK. [direction]”

Life coaches had the flexibility to use the message bank, add additional context to the bank, or develop their own content that fit the “hook + direction” template. [Appendix Section B](#) provides the initial text message bank that was developed by the school staff.

Nudges may affect students on both extensive and intensive margins. On the extensive margin, they may encourage students to remain enrolled in TEC term-over-term. While a student is enrolled in TEC, the nudges are designed to encourage students to persist through challenges and complete their classes. Both changes to these extensive and intensive margins will in principle lead to increased graduation rates.

III Experimental Evaluation

During the 2020–21 and 2021–22 academic years, a subset of students at TEC in Austin, TX was randomly selected to receive the nudging intervention from their life coaches. Students not selected for messaging continued to receive the same set of standard supports available to all students. We track student outcomes through administrative enrollment, course completion, and guidance notes data, all provided by TEC Austin.

III.A Study Design and Sample

Students entered the study during two distinct periods. When the study initially launched during the first term of the 2021 AY, students were proactively recruited by school staff to participate in a research study about new Excel Center services designed to improve persistence, completion, and post-graduation outcomes. Interested students completed a baseline survey and were subsequently randomized into treatment and control arms.¹⁰ During this time, enrollment into the study occurred during four of the five terms of the 2020–21 academic year: September 2020 (term 1); October 2020 (term 2); January 2021 (term 3); and April 2021 (term 5). Randomization was stratified by three campuses—Norwood, American YouthWorks (AYW), and South Austin—and each term students were assigned to receive nudges at a 2-to-1 ratio. During these four waves of randomization, 116 students were assigned to the treatment group and 57 were assigned to the control group.

Study enrollment changed during the 2022 AY. During this school year, all currently enrolled students were eligible to be randomized into the intervention.¹¹ During the second term of the 2022 AY (October 2021), Goodwill staff provided the research team with all currently enrolled students. Randomization occurred among those who had not yet been randomized into the study. Randomization was stratified by life coach and gender. During this round, each life coach would be assigned 25 students with which to message, and those 25 spots were proportionally divided between their male and female students based on their caseload. For example, if 40 percent of a life coach’s students were female, then 10 of the 25 spots

¹⁰Our study is registered under study ID [AEARCTR-0006383](#) with the AEA RCT Registry. The initial study design included two treatment arms and a control arm. The first treatment arm was the light-touch text message intervention. The second treatment arm was designed to be more intensive. Students were intended to work with a college and career readiness coach (CCRC) in a workshop setting to help them map out their post-secondary career path. These students also received the text message nudge. Because of the challenges posed by the COVID-19 pandemic, the CCRC intervention faced implementation challenges: students had little engagement with the CCRC, and few enrolled in the weekly job readiness seminar/workshop. Because of the non-existent take-up of this portion of the intervention, we pool the data of both treatment arms in this study.

¹¹The original study design sought active participation in order to maximize take-up of the CCRC intervention. Once it was clear the CCRC intervention would not continue, we expanded the study pool to include all students in order to increase the study’s sample size and the share of students who could be served by this additional service.

would be randomly allocated to their female students and 15 of the 25 would be allocated to their male students. Gender-specific caseloads varied from 9 to 62 students, and the resulting within-strata treatment probability ranged from 30 to 60 percent. A similar procedure was followed during the final period of randomization conducted during the fourth term of the 2022 AY (February 2022), and 12 students for each life coach were randomly allocated to the treatment group. During these two final waves of random assignment, 287 students were assigned to the treatment group and 435 were assigned to the control group. [Appendix Table A-1](#) summarizes the number of individuals randomized throughout the study and provides some descriptive statistics on the treatment probability within each stratum.

Baseline characteristics appear to be balanced across treatment groups. [Table 1](#) reports mean student characteristics (Panel A) and pre-treatment outcome variables (Panel B) for control and treatment groups in columns (1) and (2), respectively. Column (3) reports the randomization strata-adjusted difference between groups. A little over a quarter of students are male, one in ten are white, about one in five are black, and nearly two-thirds are Hispanic. The typical student is about 28 years old and had been enrolled at the Excel Center for about 1 to 2 terms prior to the school term in which they were randomized. Many pre-randomization outcomes are well-balanced, though the treatment group had been enrolled for 0.2 terms longer and had 1.1 additional case note in their record prior to randomization. Our analysis directly controls for these characteristics to account for these small imbalances.

III.B Data

We make use of a number of administrative datasets collected by Goodwill of Central Texas. School records provide student-level information on demographics, time of initial enrollment, and the date of graduation (if applicable). We also make use of additional records on entry and withdrawal (date of entry, date of exit, reason for withdrawal, campus of enrollment), course completion records, case notes collected by school staff (e.g., interactions with and notes from life coaches, documentation of the delivery of the nudging intervention), and timestamped login information from the Excel Center’s online student platform.

Using these data, we construct a balanced panel of outcomes in event time. For each student, we measure a set of outcomes observed in a particular school term. Term 0 represents the term in which an individual was randomized. For all students, we can observe outcomes measured during the five terms before random assignment through at least ten terms (or two academic years) following random assignment. Our two primary outcomes of interest are indicators for whether a student is enrolled in a given term and whether

a student has graduated by a given term. We supplement these outcomes with information on credits completed and counts of guidance notes recorded (separated by type) in order to explore mechanisms. We also summarize our results by collapsing the panel into a cross-sectional data set with cumulative outcome measures (e.g., an indicator for whether the student graduated by term ten or total math credits completed by term ten). Unless otherwise noted, the cross-sectional dataset consists of observations ten terms post treatment-assignment.

III.C Nudge Delivery and Timing

Guidance case notes data confirm that random assignment created meaningfully large differences in whether a student received text messages and how many text messages they received. [Figure 1](#) plots text message receipt rates by term for the treatment and control groups. The horizontal axis depicts academic term relative to when a student was randomized (term 0). The top panel (a) reports the share of the treatment group (solid lines with navy circles) and control group (dashed line with gold diamonds) that received a nudge during the term.¹² During the first term over 70 percent of the treatment group received a nudge from their life coach.¹³ The bottom panel reports the average number of nudges sent to students in the treatment and control groups. Early in the intervention, the typical student was receiving about 1.5 to 2.5 nudges. This equates to about 3 nudges per term for enrolled students, shy of the weekly goal during the 8-week term. [Figure 1](#) also documents that students in the control group were much less likely to have been sent a nudge by their life coach, though the number of nudges sent increased to nearly 0.5 messages after about 4 terms, indicating imperfect compliance with the nudging experiment. Our realized text-message dosage was lower than the messaging frequencies reported in other educational nudge experiments. [Chande et al. \(2015\)](#) sent adult learners three messages during an initial one-week break and one message per week thereafter. [Castleman and Page \(2015\)](#) sent college-intending high school graduates approximately one message every five days over the summer, while [York, Loeb and Doss \(2019\)](#) sent parents of preschoolers three messages per week over eight months.

[Table 2](#) describes the overall implementation of the intervention and how the types of nudges that were sent were broken down by the four categories described in [Section II.B](#). Columns (1) and (3) report the

¹²Between academic terms, there is usually a one-week break period, as well as a typical summer break. When defining whether a case note was recorded during a particular academic term, we consider case notes that were recorded after the end date of the previous term and before the end date of the respective term.

¹³A small number of control and treatment students received nudges prior to treatment assignment. These nudges were sent in error; life coaches either sent nudges en masse to all their students or because the life coach sent a personalized message containing content in the text-message bank. Of the over 6000 nudges sent to treated students only 116 were sent in pre-treatment periods.

share of students receiving at least one message in the control group and treatment group, respectively, while columns (2) and (4) similarly report the total number of messages received on average. Through the 10th term following random assignment, 86.8 percent of the treatment group had received at least one nudge compared to 32.7 percent in the control group. This difference resulted in the treatment group receiving 10.8 nudges relative to the 2.4 in the control group. The two most common types of messages sent to the treatment group were related to encouraging persistence (3.5 messages) and the benefits of completing TEC (2.5 messages), with fewer nudges related to post-secondary opportunities (1.1 messages), program requirements (1.5 messages), or other communications (2.3 messages) being sent.

IV Empirical Strategy

We leverage the experimental design and estimate ITT effects of being assigned to receive text nudges using the following linear regression specification:

$$y_i = \beta D_i + \psi_{s(i)} + X_i\Gamma + \epsilon_i \quad (1)$$

where y_i is an outcome for student i and D_i is an indicator that takes the value of 1 for students assigned to the treatment group and 0 for individuals assigned to the control group. The vector $\psi_{s(i)}$ is a set of stratification fixed-effects to account for the fact that randomization occurred separately by term and campus (during the first academic year) or by term and life coach-gender (during the second academic year); treatment probability changed within-strata as a result. In addition to this parsimonious specification, we also include an additional set of baseline controls X_i measured in the term prior to random assignment. This vector includes demographic controls for gender, race/ethnicity (white, black, and hispanic), and age. We also control for school characteristics observed prior to random assignment: the type of high school degree being pursued, number of terms enrolled, number of logins to the online student portal, number of total credits completed, and number of credits completed at the Excel Center. These variables are used to adjust for baseline imbalances and to improve precision. Throughout our discussion of results, we present estimates with and without these additional controls.

The coefficient β provides the conditional difference in average outcomes between students assigned to treatment and control groups. Because of random assignment, this difference can be interpreted as the causal effect of being assigned to receive the nudging intervention (i.e., the intent-to-treat effect). However,

Section III.C documented that while the majority of the treatment group (87 percent) received at least one nudge, a small share of the control group did as well. To account for this noncompliance, we present instrumental variables estimates of the effect of receiving at least one nudge. We calculate these estimates using the following two-stage least squares specification with the first and second stage regressions given by:

$$T_i = \alpha D_i + \phi_{s(i)} + X_i \Gamma + \nu_i \quad (2)$$

$$y_i = \delta \hat{T}_i + \psi_{s(i)} + X_i \Lambda + \omega_i \quad (3)$$

where T_i is an indicator for whether the student ever received a nudge after treatment assignment. Under the standard IV assumptions, δ can be interpreted as the local average treatment effect of receiving at least one nudge among the compliers, that is, among the students who would have only received the nudge when assigned to the treatment group.

V Impact of Nudges on Enrollment and Graduation

V.A Trends by Treatment Assignment

The goal of the nudging intervention was to encourage students to remain enrolled and engaged at the Excel Center, leading to an increase in degree completion. Figure 2 depicts trends in term-by-term enrollment rates (Panel a) and graduation rates (Panel b) by treatment status. The horizontal axis in the figure plots academic terms relative to the term in which a student was randomized, with the dashed vertical line indicating randomization assignment.

During the five pre-policy terms, roughly 20 percent of students were already enrolled at the Excel Center.¹⁴ Nearly 90 percent of students were actively enrolled in the term they were assigned to treatment. Naturally, enrollment declines in the following ten terms as students either drop out of or graduate from TEC. Enrollment declines occur similarly in both the treatment and control groups, and we find no statistically significant differences in enrollment across the two groups in any of the post-treatment terms (Panel c).

A null enrollment effect does not necessarily imply no effect of the nudge on TEC graduation. On the one hand, nudges could affect some students on the extensive margin, prompting them to continue enrolling in TEC each term. However, the nudges may also impact students on the intensive margin, encouraging

¹⁴A student is defined as enrolled in TEC if they remain enrolled for at least four weeks of a given term.

them to persist through challenges associated with completing coursework. Unlike the pattern of results on enrollment, we do find meaningful differences in graduation rates emerging over time. While graduation rates increase over time for both groups, a divergence emerges five terms following random assignment. By the end of the 10th term following random assignment, roughly 30 percent of the treatment group graduated from TEC, 6.7 percentage points higher than the control (Figure 2 Panel d). This difference, apart from being large in magnitude, is also statistically significant at the 95% level ten terms after treatment assignment.

V.B Main Enrollment and Graduation Results

We next turn to our ITT and IV effects to discuss the significance and magnitude of the text nudge on our enrollment and graduation outcomes of interest (Table 3). The table considers four outcomes: total number of terms enrolled since random assignment, an indicator for whether students either graduated or were still enrolled through relative term 10, an indicator for whether a student graduated by relative term 10, and the total number of terms the student completed 1 or more credits. Column (1) reports the control group mean of the outcome. Columns (2) and (3) report ITT estimates from a specification with only randomization strata fixed effects and additionally with baseline controls, respectively. Column (4) reports IV estimates using the same set of baseline controls. Column (5) reports the relative change in the outcome from column (4) relative to the control group mean.

Consistent with enrollment trend results (Figure 2), we find no evidence the nudging intervention increased the total number of terms students remained enrolled in the Excel Center, but that there was a substantial graduation effect. By the end of the analysis window, 9.3 percent of the control group remained enrolled in TEC and an additional 22.6 percent graduated. The treatment group is 4.7 percentage points more likely to either have graduated or remain enrolled in TEC (column 3) by the end of the analysis window, with all of this effect coming from the effect on graduation (4.9 percentage points, $p < 0.10$). When instrumenting for receipt of a nudge with assignment to the treatment group (column 4), we find an IV effect on graduation of 9.3 percentage points ($p < 0.05$). Notably, this effect is a 41 percent increase in the likelihood of graduation relative to the control group graduation rate of 22.6 percent.

Our 9.3 percentage point graduation effect is larger in magnitude relative to similar research settings. Among traditional-age high school students, Lichand, Christen and van Egeraat (2023) find no statistically significant average reduction in dropout risk from text messages, while Theodos et al. (2016) find no

statistically significant overall effect on high school graduation from a broader program combining paid internships, training, and coaching.¹⁵ In the community college context, however, O’Hara and Sparrow (2019) find nudges increased term-over-term re-enrollment by 7 percentage points.¹⁶ Other studies of nudges on college enrollment, credit completion, and course attendance, all factors contributing to successful graduation, find smaller or zero treatment effects compared to our setting (Oreopoulos and Ford, 2019; Avery et al., 2021; Castleman and Long, 2016). Our larger estimate likely reflects that messages came from a coach the student already knew, could be tailored to the student, and pointed to support services the school already offered, features we return to in Section VIII.

V.C Nudges and Excel Center Completed Credits

To better understand the positive graduation treatment effect, we explore course completion among treatment and control students using TEC transcript data. We estimate both our ITT and IV specifications, replacing our outcome with the total number of credits a student completes while enrolled at TEC in post-treatment terms. We explore all completed credits, as well as credits completed by subject. Non-core credits are compared separately. The results are presented in Table 4, which follows the same format as Table 3.

Treated compliers complete 0.49 extra credits while enrolled at TEC, a ten percent increase from the control group mean of 4.75 credits. Students specifically increase the number of completed credits in core-subject areas, especially in reading and social studies, when compared to the control group. However, these estimates are statistically insignificant, as we are underpowered to detect effects of this size.

Although the mean credit estimate is imprecise, modest average gains could conceal larger changes among students close to completing their remaining requirements. To address this possibility, we explore the distribution of completed credits at TEC by treatment group in Figure 3. Panel (a) plots all credits completed, panel (b) core credits, and panel (c) non-core credits. In each subplot, we report the p -value for the Kolmogorov-Smirnov test for distributional equality. Treatment group students are less concentrated between 0 and 3 completed credits and more concentrated between 4 and 20 completed credits relative to the control group (Panel a). This pattern suggests that the nudges induced some students to complete

¹⁵Lichand, Christen and van Egeraat (2023) estimate a 22 percent reduction in dropout risk among students with below-median baseline achievement, but this estimate is statistically insignificant ($p = 0.47$). Their messages targeted students or their caregivers. Theodos et al. (2016) estimate a 4 percentage point increase in high school graduation among male students, although this estimate is not statistically significant after adjustment for multiple comparisons.

¹⁶Term-over-term re-enrollment increased by up to 10 percentage points for STEM students. Given the primary outcome is re-enrollment, the net effect on graduation is likely to be below our treatment effect in magnitude.

the credits required for graduation, rather than merely encouraging many students to complete a marginal number of additional courses. This interpretation is further supported by the fact that the upper tail of the treatment group credit distribution remains above that of the control group across the full support of the distribution. Panels (b) and (c) show this pattern holds for both core and non-core classes.¹⁷

V.D Nudges Did Not Crowd-In or Crowd-Out Other Supports

The nudging intervention did not crowd in additional interactions with school support staff (Figure 4). Because every staff contact with a student generates a case note, the count of case notes in a term measures how much support a student received from school staff. We exclude the notes that document the nudges themselves, so the counts capture all other forms of contact. Trends in the number of case notes recorded by term are very similar between the treatment and control groups (Panel a).. We see a similar pattern of overlapping trends when focusing on case notes recorded by the life coaches at the school (Panel b) or case notes that were coded as “attendance-related” case notes (Panel d). Panel (c) reports case notes recorded by alumni coaches, the staff who work with students after they graduate on college and job placement. Alumni coaches are distinct from the life coaches who delivered the intervention, and a student is assigned one only upon graduating. Here we do see a difference between groups, which is consistent with the intervention’s effect on graduation. The number of alumni coach case notes diverges between treatment and control and the gap persists throughout the panel. As with graduation rates, we see a divergence in the number of alumni coach case notes that persists throughout the panel. There is a large spike in alumni coach case notes in the fourth term following randomization. The majority of our sample was randomized in Term 2 of the 2021–22 AY. For these students, relative term 4 would include the summer following the school year, a period where a number of students would have just graduated at the end of the academic year.

V.E Student and Campus Heterogeneity

We next examine whether the impact of the text-nudge intervention varied across different subgroups of students.¹⁸ For each subgroup, we estimate our primary IV specification with controls, using graduation within 10 terms of treatment assignment as the outcome. Figure 5 plots the estimated complier treatment effects, with horizontal bars denoting 95% confidence intervals.

¹⁷Core classes include mathematics, English/language arts, science, and social studies.

¹⁸Subgroups are divided by racial factors, age, degree type, treatment wave, and campus.

Figure 5 presents subgroup-specific point estimates across many potential subgroups as a way of characterizing potential underlying heterogeneity, though the sample size of 895 students limits our ability to draw precise conclusions. In general, most subgroup estimates are centered around the full sample estimate. The estimated effects tend to be slightly larger for white students, older students, female students, students with more attempted and completed credits prior to treatment assignment, and students who were enrolled at TEC before treatment assignment. Consistent with Figure 3, these patterns suggest that the text nudges may have been most effective for students near the margin of graduation, helping them complete the remaining credits required to earn a diploma. In addition, the larger estimated effects for students already enrolled at TEC suggest that the intervention may have complemented previously established relationships built between students and their life coaches.

By contrast, the estimated effects are smaller and close to zero for younger students, male students, and students attending the South Austin Campus, among other groups. Existing evidence on gender heterogeneity in text-nudge interventions is mixed, though Castleman and Page (2015) and O’Hara and Sparrow (2019) find that nudges were more effective at promoting college enrollment among male students. The smaller estimated effects for students entering with fewer completed credits may also reflect the greater difficulty of moving students who remain farther from graduation. However, the estimates for these subgroups are imprecise and we estimate effects across many subgroups, which limits our ability to conclude that the intervention was less or ineffective for these populations.

VI Exploring Mechanisms

Evidence in Section V shows that the nudging intervention increased course completion and diploma attainment. In this section, we explore the potential mechanisms through which the nudges may have increased graduation rates.

Although the experiment was not designed with multiple treatment arms to test various causal channels, we can exploit one design factor to understand mechanisms. Because students’ life coaches deliver the intervention, its effectiveness may vary with how coaches implement it; theory and prior evidence point to two relevant channels. First, students assigned to coaches who send nudges more frequently may make the nudge contents more salient, increasing the likelihood of graduation. This prediction aligns with Damgaard and Gravert (2018) and Antinyan et al. (2021), who respectively show that higher nudge frequency increases charitable giving and the completion of delinquent tax returns. Second, human-capital theory (Arrow, 1962;

Becker, 1993) and evidence on returns to experience in education (Ladd and Sorensen, 2017; Papay and Kraft, 2015) suggest that more experienced coaches may implement the intervention more effectively, for example by tailoring messages that keep students engaged with TEC.

Motivated by these literatures, we examine heterogeneity in graduation effects along the dimensions of life-coach salience and experience. To proxy for salience, we compute for each coach the average number of nudges sent to treated students during their first term. When constructing this measure of salience, we exclude students who do not remain enrolled for the full term.¹⁹ Our measure of salience assumes that coaches who send more nudges in the first term continue to do so in later terms. We refer to this measure as a coach’s nudge dosage and report it in Table 5. Nudge dosage varies substantially across coaches, ranging from roughly 1 to 5 nudges per treated student, with a mean of 3.22. We label a life coach (LC) as high-dosage if their nudge dosage is above this average.

We define an experienced life coach as someone who advised at least one student in the three years prior to when we first implemented the intervention in September 2020.²⁰ Table 5 shows that six of the ten coaches had prior experience. Experienced coaches on average advise 422 students and graduate 136, for a graduation rate of 32.2 percent, over this time period. This rate exceeds the control-group mean of 22.6 percent, although the two are not directly comparable across time because of the COVID-19 pandemic.

To assess whether the graduation effect varies across LC nudge dosage, we estimate the following model:

$$Y_{iks} = \beta_l \text{LowNudge}_k \times \text{Treat}_i + \beta_h \text{HighNudge}_k \times \text{Treat}_i + \varphi_{s(i)} \\ + X_i \Lambda_l \times \text{LowNudge}_k + X_i \Lambda_h \times \text{HighNudge}_k + \varepsilon_{iks}. \quad (4)$$

Index k denotes the LC assigned to student i . LowNudge_k and HighNudge_k indicate assignment to a low- or high-nudge LC. Interacting these indicators with the treatment variable allows β_l and β_h to be interpreted as treatment effects conditional on LC nudge-intensity assignment.²¹ Baseline covariates are allowed to have differential effects by LC type through interactions with LowNudge_k and HighNudge_k . We estimate the same model for exploring experience, substituting in indicators for LowExperience_k and HighExperience_k in lieu of the nudge dosage variables.

¹⁹If some coaches are assigned students with higher attrition risk, including such students would mechanically lower measured nudge dosage.

²⁰Our data prevent us from directly observing the life coach each student is paired with prior to the implementation of the nudge intervention. We proxy for coach-student pairings by observing if there is at least one case note between student and life coach in this time period. We exclude any pre-policy-implementation student-coach pairings where the student was part of the intervention.

²¹More precisely, these coefficients capture ITT effects conditional on LC assignment.

Panel A of Table 6 provides little evidence that variation in LC nudge dosage explains the overall treatment effect on graduation.²² Column (1) shows estimates of β_l , with column (2) estimates of β_h . Column (3) reports the difference between these two parameter estimates, along with the corresponding standard error. Treatment-group students assigned to below-mean and above-mean nudge-dosage LCs are 4.5 and 4.7 percentage points (ITT) more likely to graduate from TEC, respectively. Although both estimates are economically meaningful, they are not statistically distinguishable from one another. These findings suggest that the intervention may operate through the extensive margin—assignment to the treatment—rather than the intensive margin—the number of nudges received. However, our experimental design limits our ability to draw this conclusion definitively, because it did not include a treatment arm designed to test this mechanism. Despite this limitation, the notion that high-dosage LCs continue to send more nudges to treatment students throughout their enrollment is supported by panel B.

Columns (4) to (6) mirror the format of columns (1) to (3), where students are split by assignment to low and high-experienced LCs. Text nudges delivered by experienced LCs increase graduation rates by 6.7 percentage points, a 31 percent increase relative to the control group mean of 21.6 percent (Panel A). The corresponding estimate for inexperienced LCs is 1.4 percentage points, or only a 6 percent increase relative to the control mean. These results suggest that LC experience, rather than nudge volume, is a key driver of the graduation effect. However, while economically meaningful, the difference across life coaches is not statistically distinguishable from zero. We explore several channels associated with life-coach experience in the following subsections.

VI.A Nudge Choice

LCs were given discretion over the content of messages sent to treatment students. Although experienced and inexperienced LCs send texts at similar rates, the composition of those messages differs. Panel B columns (4) to (6) show that treated students assigned to experienced LCs on average received 0.19 fewer texts per enrolled term related to program benefits compared to inexperienced LCs. Meanwhile, experienced LCs sent 0.10 more texts per term highlighting post-secondary opportunities and related resources to treated students compared to their inexperienced peers. If most students are already aware of the benefits of earning a degree but have limited information about how to obtain those benefits, such as enrolling in post-secondary education, the pattern would be consistent with an information-based

²²16 students were assigned to life coaches that left TEC in the students' first treatment term. We could not verify the new LC these students were assigned to, and remove them from the sample for this analysis.

mechanism driving the observed treatment effects. However, the magnitude of these differences is small and unlikely to explain the large differences in graduation treatment effect by LC experience.

VI.B Engagement with TEC Resources

Figure 4 suggests the text nudges did not complement or substitute for traditional LC-to-student communications. However, overall trends mask communication heterogeneity by LC experience. Panel C of Table 6 shows that this holds within each coach type as well. The intervention has no detectable effect on the number of non-nudge contacts a student has with school staff, whether the coach is experienced or not, and the point estimates are small relative to control means of 7 to 12 contacts per term. The one exception is contact with academic advisors, where treated students of inexperienced coaches had slightly fewer contacts and those of experienced coaches slightly more. The difference is statistically significant but amounts to about a tenth of a contact per term, too small to account for the gap in graduation effects by coach experience.

Treatment-group students assigned to experienced LCs log into the Skyward portal significantly more often compared to treatment-group students assigned to inexperienced LCs.²³ The estimated increase of 3.33 logins per term for treatment-group students assigned to experienced LCs represents a 31 percent rise relative to the appropriate control-group mean, an effect comparable in magnitude to the overall graduation impact. This pattern is consistent with an information-based mechanism: if experienced LCs provide more information about student resources and post-secondary options, students may become more engaged with the platform and, in turn, more motivated to complete their diploma. The login results align with prior evidence that light-touch interventions can shift perceptions of and persistence into post-secondary education, though, to our knowledge, this study is the first to document these nudges have effects on high-school graduation (Castleman and Page, 2015; Hyman, 2020; Peter and Zambre, 2017).

VI.C Nudge Customization and Content

Life coaches, apart from sending nudges from the provided bank, were also allowed to create custom messages. Because some of the largest effects in prior work come from personalized messages, we test whether experienced life coaches send nudges with more customized content (Castleman and Page, 2015; Page, Castleman and Meyer, 2020; Dynarski et al., 2021). Using the case-note data, we determine whether

²³The Skyward portal is an online platform through which students communicate with their LC, access grades and academic records, and view TEC resources.

the nudge is a combination of hooks and directions from the initial message bank, or if the nudges were LC-created. We also note whether the nudge specifically mentioned the student’s name or had links to additional program resources, as well as the number of words in the nudge. We explore these factors using the same heterogeneity model.

Table 7 mirrors the format of columns (4) to (6) in Table 6. Experienced life coaches are significantly less likely to send nudges from the given message bank (0.33 fewer per enrolled student) and more likely to send nudges with customized content (0.33 more nudges per enrolled student) compared to their inexperienced peers. Experienced LCs also send shorter nudges of about nine fewer words on average. These results imply experienced life coaches are familiar with what students need to remain involved and engaged with their classes, perhaps sending a specific nudge when students need them most.

VII The Implied Earnings Benefits of Text Messages

To contextualize the graduation effect of our intervention, we link TEC students who started at the Excel Center between August 2014 and March 2020 ($N = 2,567$) to administrative earnings data to directly measure the earnings impact of completing a diploma. For this sample of individuals, we can observe a balanced panel of earnings during the two years prior to starting at the Excel Center through the four years after initial matriculation.

Unemployment insurance earnings records come from the Texas Workforce Commission through a data partnership with the Ray Marshall Center at the University of Texas at Austin. We limit our analysis sample to students for whom we observe a valid social security number from the TEC records and assume that if we do not observe earnings for an individual in a given quarter that they had no earnings in that quarter. Given this assumption, our outcome of interest measures formal-sector (i.e., earnings covered by the UI system) earnings in the state of Texas. This outcome does not capture any non-UI covered earnings (e.g., contract work) or earnings earned outside of the state of Texas. For each student, we construct a panel of earnings in event time where “quarter 0” represents the calendar quarter during which they first enrolled in the Excel Center.

We use this observational data to estimate a nonexperimental specification following Brough, Phillips and Turner (2024) that compares graduates to enrolled non-graduates, controlling for differences in pre-

enrollment labor market history. Specifically, we estimate the following ordinary least squares regression:²⁴

$$Y_{it} = \beta_t G_i + X_i \Gamma + \tau_{q(i)} + \epsilon_{it} \quad (5)$$

where Y_{it} is earnings for individual i observed t quarters following initial Excel Center enrollment. X_i is a vector of controls that includes indicators for race and ethnicity (Black, Asian, American Indian, Hispanic, and White) along with indicators for employment during each of the eight quarters preceding enrollment and the level of earnings in each of those eight quarters. We select among these controls using the post-double selection LASSO procedure of [Belloni, Chernozhukov and Hansen \(2014\)](#). $\tau_{q(i)}$ is a vector of initial enrollment quarter, $q(i)$, fixed effects, which makes comparisons between students who started at the Excel Center during the same calendar quarter. When visually presenting earnings trends to motivate the research design, we weight the sample by inverse propensity weights that non-parametrically adjust for observable selection based on prior employment and earnings, race, and start quarter.²⁵

For β_t to identify the causal effect of graduation, our approach assumes that, conditional on prior labor market history, race, and starting quarter, whether a student graduates is unrelated to their subsequent potential labor market earnings in the absence of graduation. A number of recent papers have documented that conditioning on rich administrative earnings data does a good job of uncovering causal effects in this setting ([Grosz, 2020](#); [Leung and Pei, 2020](#)). Moreover, [Brough, Phillips and Turner \(2024\)](#) provide a number of robustness checks to demonstrate that non-graduating applicants to the Excel Center provide a reasonable comparison group for the counterfactual earnings of graduates. One difference in our setting is that we do not have access to data on non-enrolled applicants. Because enrolled students may be partially treated, our approach may underestimate the total effect of enrolling and completing an Excel Center diploma.

[Figure 6](#) reports the results of this analysis. Panel (a) reports weighted trends in average earnings. During the two years prior to enrollment, students earn roughly \$2,000 to \$2,500 each quarter. Propensity weights generate two groups with similar levels and trends in earnings during those two years. During the year following enrollment, graduates experience a relative decline in earnings. This decrease could be

²⁴One could directly estimate the LATE of graduation on earnings by instrumenting graduation with assignment to treatment. However, given the available sample size and a first-stage effect of treatment assignment on graduation of only 4.9 percentage points, the resulting estimates are too imprecise to be informative. We therefore use an estimator from [Brough, Phillips and Turner \(2024\)](#) to quantify the earnings effects of graduation.

²⁵Specifically, we estimate a logit model of graduation on the 16 pre-enrollment employment and earnings measures, race indicators, start quarter fixed effects, and indicators for age decile. The inverse propensity weight is then given by $w_i = \frac{G_i}{p_i^{Grad}} + \frac{1-G_i}{1-p_i^{Grad}}$.

the result of being more likely to leave the workforce or scale back on hours while focusing on education. Roughly two years after enrollment, around the time when the typical student graduates, earnings for graduates begin to overtake their counterfactual earnings. During the 4th year following enrollment, quarterly earnings are roughly \$600 to \$700 higher than they would have been in the absence of graduating. This effect magnitude is in line with the estimates found in [Brough, Phillips and Turner \(2024\)](#) when comparing graduates to enrolled non-graduates. Summing these quarterly earnings differences (i.e., the losses in earlier quarters and gains in later quarters) to present value using a 3 percent annual discount rate means that graduates earned roughly \$1,600 more during the four years following enrollment, even when including the foregone earnings while in school. The nudging intervention increased the likelihood of graduating by 9.3 percentage points among compliers—meaning it increased pre-tax earnings by roughly \$149 over the same time period.

This implied earnings benefit relies on the observed effects seen during the four years following enrollment, but the returns to graduation likely persist beyond that time horizon. After four years, graduates are earning roughly \$600 more per quarter or \$2,400 per year compared to non-graduated TEC enrollees. Assuming that graduation effect persists until retirement (or 40 years following enrollment) provides a potential upper bound on the overall impact. The accumulated earnings increases translate to a roughly \$48,000 increase in present value of lifetime earnings from graduation.²⁶ Combining this back-of-the-envelope calculation with the experimental effect of text message receipt on graduation would imply a lifetime earnings benefit of nearly \$4,500 from the text message intervention.

VIII Discussion

This study evaluates a randomized controlled trial of a light-touch nudging intervention designed to increase graduation rates among adult high school students at the Goodwill Excel Center in Austin, Texas. Targeted messages sent throughout the term by life coaches increased graduation rates by 4.9 percentage points among the treatment group; IV estimates suggest a 9.3-point increase in graduation among treated compliers, a 41 percent increase relative to the control mean. The evidence suggests that these gains were driven by increased persistence in completing courses during enrolled terms, rather than by increased enrollment in additional terms. The intervention builds on existing relationships between students and life

²⁶This calculation assumes the \$2,400 pay disparity remains constant over time during year 5 through 40 following enrollment, discounted back to year 0 at an annual 3 percent discount rate.

coaches, using low-cost, scalable communication to help students maintain progress toward a diploma.

Linking these graduation gains to labor market data indicates that the returns to graduation are economically meaningful. Graduates earn more than \$600 more per quarter four years after enrolling, consistent with sizable returns documented in other settings. Because the intervention increased graduation rates by more than nine percentage points, the implied increase in average quarterly earnings is meaningful, though modest in dollar terms. If earnings gains from graduation are durable, the benefits from this intervention are relatively large. These results suggest that even small, low-cost interventions have the potential to generate persistent labor market benefits by increasing high school completion.

Several features of the educational environment likely contributed to the intervention’s effectiveness. First, many students already had established relationships with their life coaches, making them more likely to attend to messages from those coaches. This feature of our setting may explain why the treatment was more effective for students enrolled in TEC before treatment assignment. Second, life coaches could customize messages to students’ needs, making the nudges more likely to resonate. The treatment effect appears to be driven by more experienced life coaches who sent more personalized messages. Finally, TEC provides substantial resources to help students overcome life obstacles. The messages may have helped students not only by encouraging them, but also by reminding them that these resources were available. In this sense, the intervention’s effectiveness may reflect the interaction between the nudges and the broader, more-intensive support system already available to students.

These findings suggest that policies that integrate light touch communication strategies into educational programs can generate significant gains in educational attainment. Structured, personalized messages from staff members that students already know can increase course completion and graduation rates without extending enrollment duration. Because the intervention is low-cost and leverages existing personnel, similar programs may be able to implement this strategy with minimal additional resources while improving completion outcomes.

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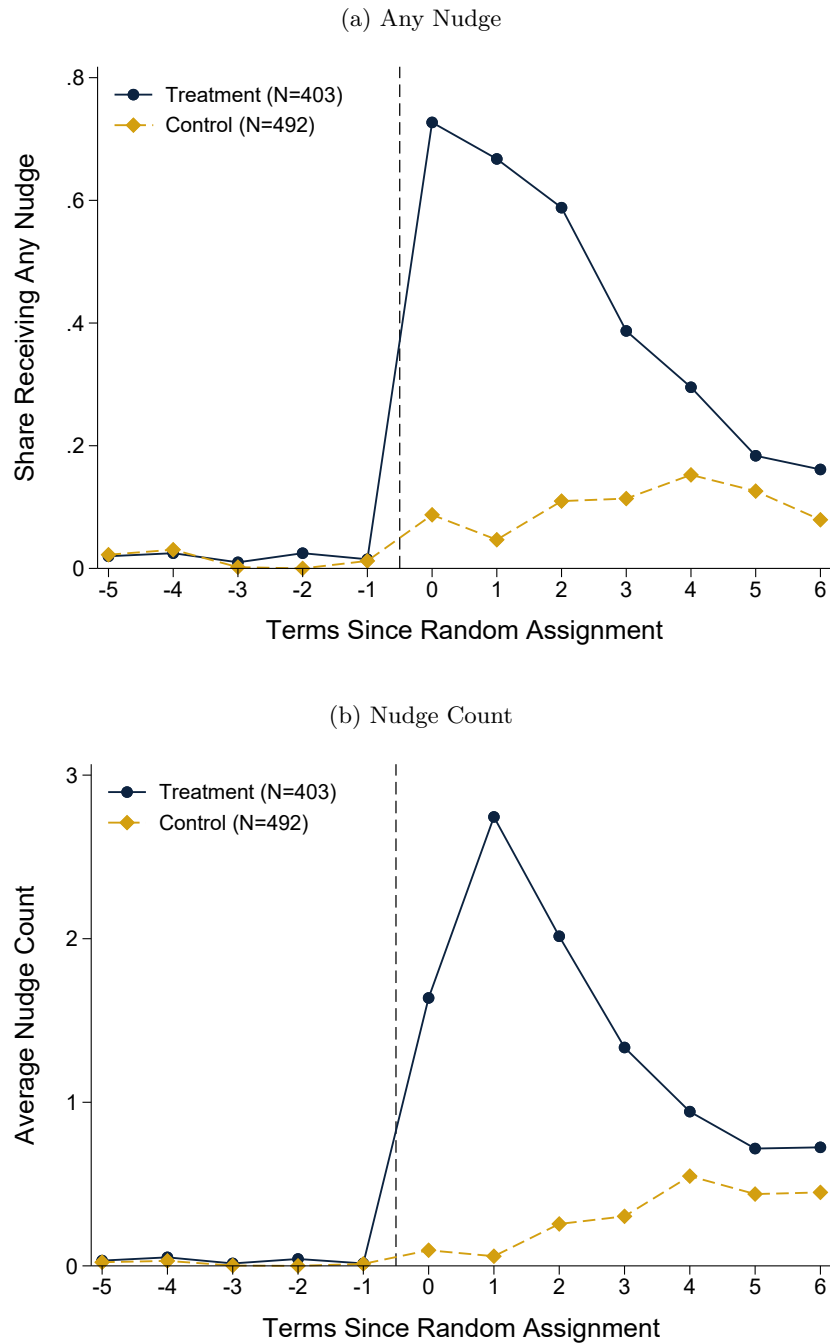
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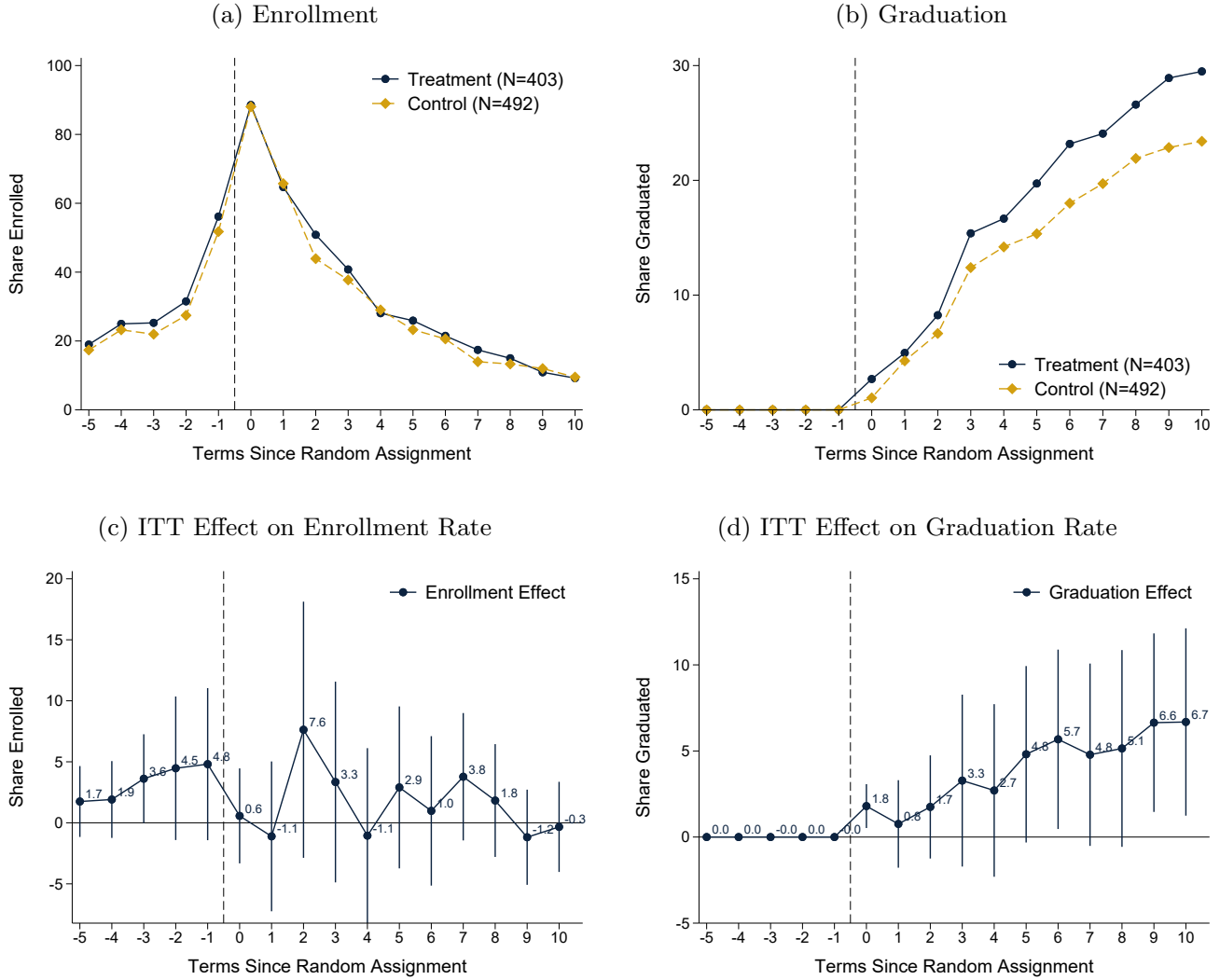
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Figure 1: Nudge Delivery and Receipt Over Time



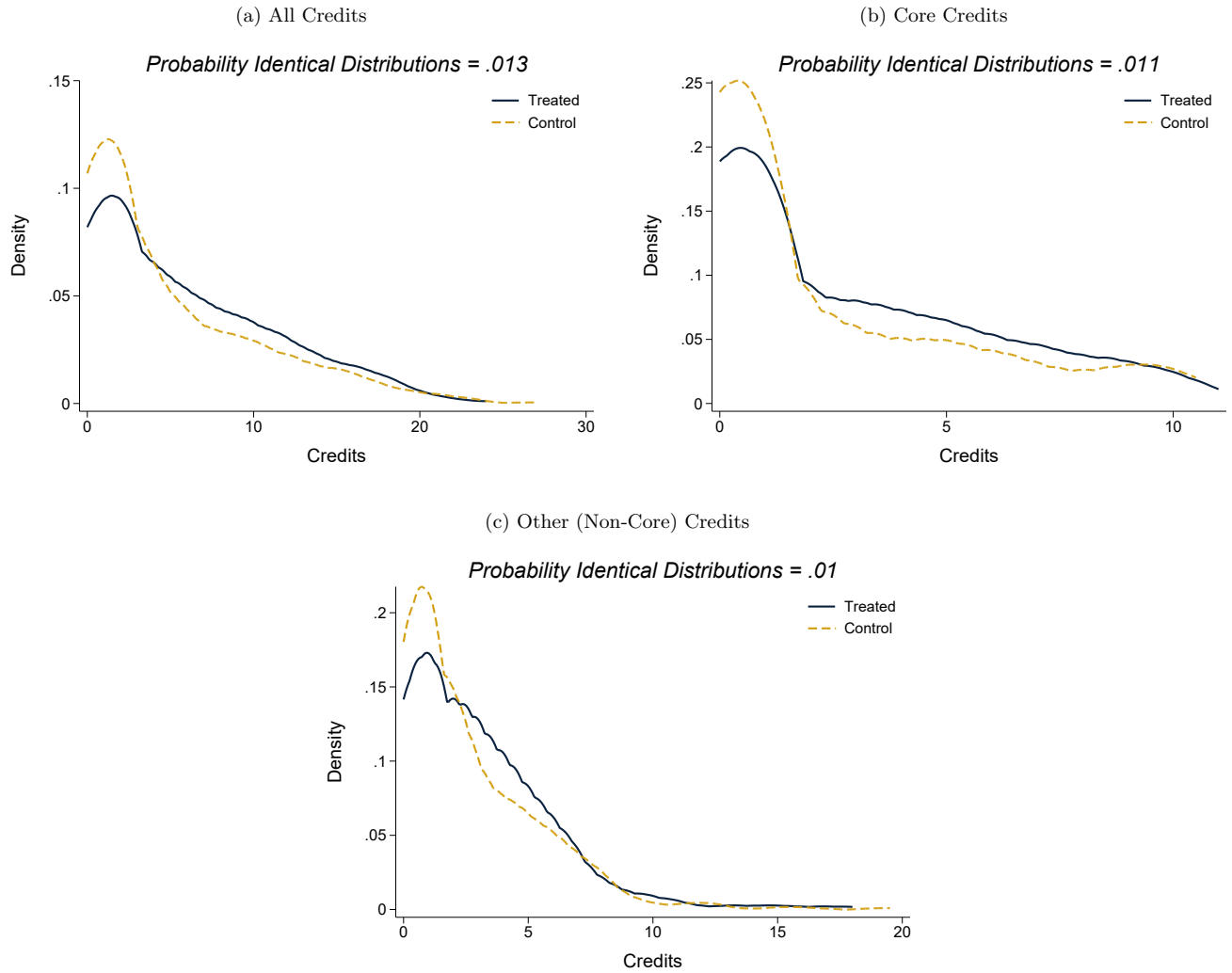
Notes: Data come from student case note records provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to receive the nudge and 492 assigned as controls. The figure plots the average number of nudges sent by life coaches in each term, where terms are made relative to randomization assignment. Term 0 represents the term which individuals were randomly assigned to the treatment and control groups. A nudge is recorded in a term if sent between the end date of the previous term and the end date of the current term. Shares/counts are plotted separately for treatment (solid navy) and control (dashed gold) students.

Figure 2: Excel Center Enrollment and Graduation by Treatment Status



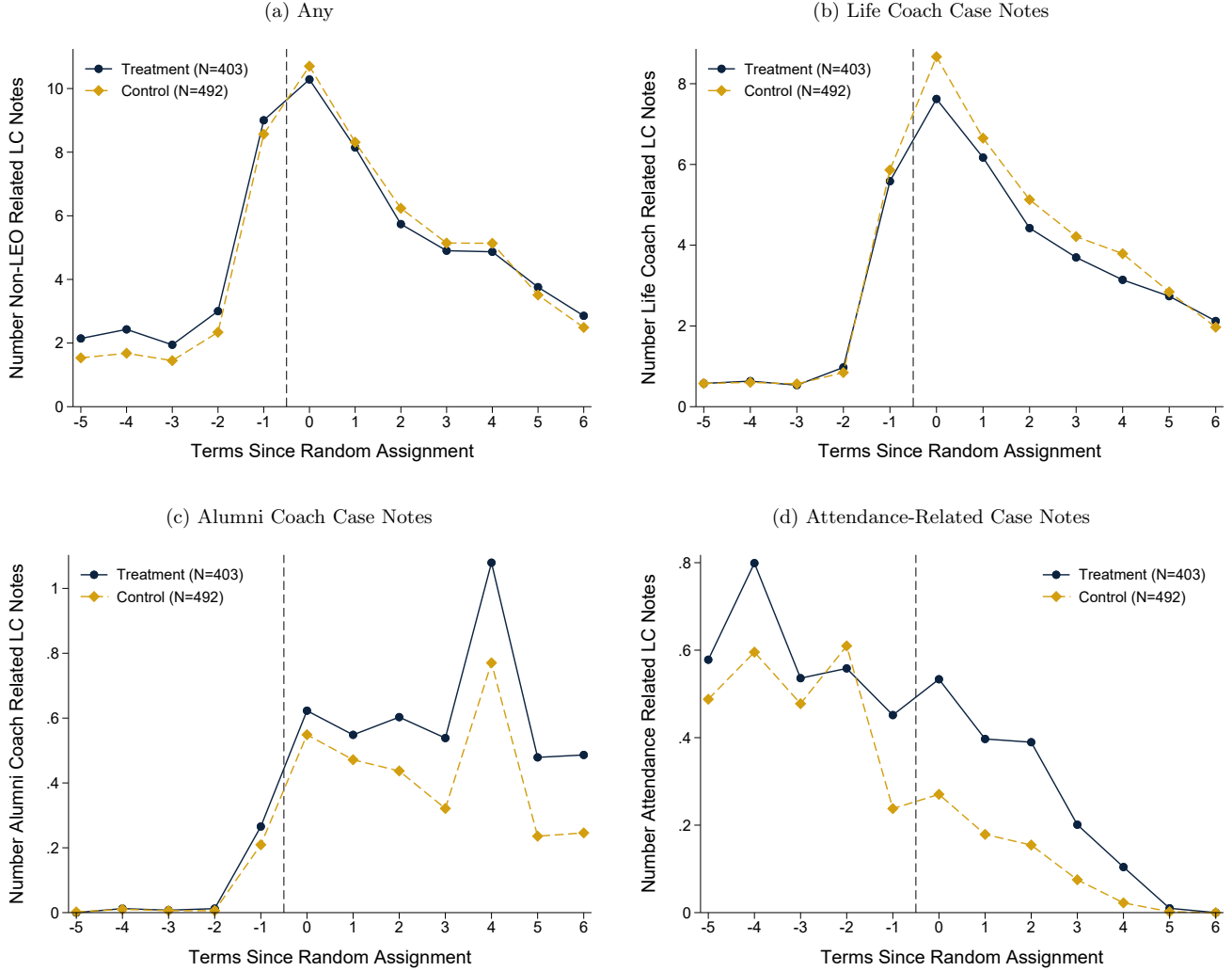
Notes: Data come from enrollment and graduation records provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to receive the nudge and 492 assigned as controls. Figures (a) and (b) plot the program enrollment and graduation rates respectively, where terms are made relative to randomization assignment. Rates are plotted separately for treatment (solid navy) and control (dashed gold) students. Figures (c) and (d) then plot the differences in enrollment and graduation effects, respectively, between treated and control students by term. 95 percent confidence intervals are reported, where standard errors are clustered by randomization strata.

Figure 3: Kernel Density Plot - Credits Completed at The Excel Center



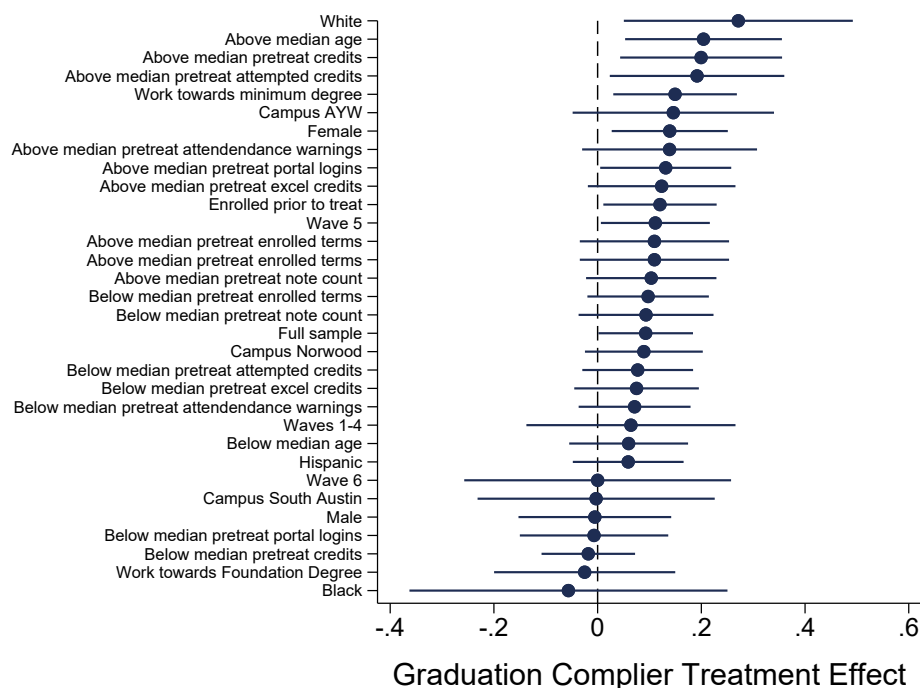
Notes: Data come from course records provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. The figures plots kernel-density estimates of the count of credits completed in the Excel Center for both treatment (solid navy) and control (dashed gold) students ten terms after a student is randomized into treatment, with the set of credits investigated denoted by figure sub captions. Equality of distributions is tested using a two-sample Kolmogorov-Smirnov test.

Figure 4: Non-Text Message Case Notes by Treatment Status



Notes: Data come from student case note records provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. Each figure plots the average number of recorded case notes in each term, where the term is made relative to random assignment. Panel (a) plots the average case-note count per term, (b) the average case-note count sent explicitly by life coaches, (c) average alumni case-note count, and (d) attendance-related case-note count. A case note is recorded in a given term if sent between the last date of the previous term and the end date of the current term. Case-note averages are plotted separately for treatment (solid navy) and control (dashed gold) students.

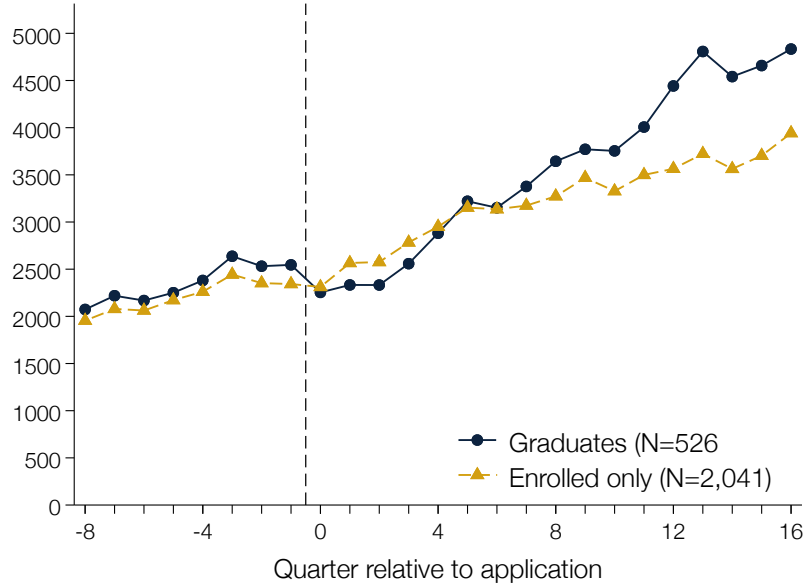
Figure 5: Graduation Treatment Effects – Heterogeneity by Campus and Student Characteristics



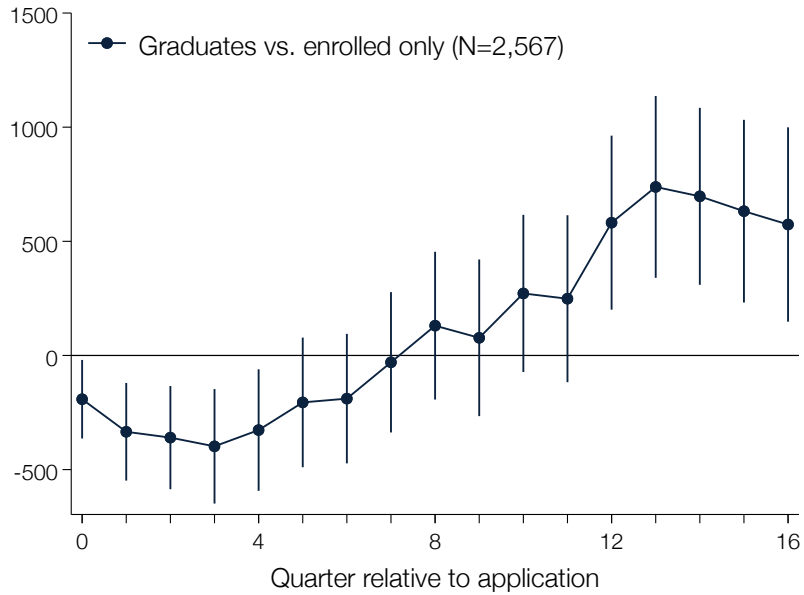
Notes: Graduation and student profile data are provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. The figure plots estimates of δ from Equation (3), the impact of the nudging intervention on students whose receipt of text messages was induced by random assignment. Students are labeled as graduated if they complete the program at most ten terms after they are randomized into treatment. For each line of Figure 5, both Equations (2) and (3) are estimated using only students who meet the stated criteria. Standardized errors are clustered at the randomization-strata level, and 95 percent confidence intervals are recorded. Confidence intervals overlapping the black dashed line indicate the estimate of δ is statistically indistinguishable from zero.

Figure 6: Earnings of Excel Center Students by Graduation Status

(a) Earnings Trends by Graduation Status



(b) Effects of Graduation on Earnings



Notes: Unemployment insurance wage records are provided by the TX Workforce Commission and accessed through the Ray Marshall Center at the University of Texas at Austin. The sample includes all TEC students who enrolled from August 2014 through March 2020 with a valid social security number, and is divided into two groups: TEC graduates (solid navy) and TEC students who did not graduate (dashed gold). Quarter 0 represents the quarter student initially enrolled in a TEC Austin campus. Panel A plots average earnings, while Panel B presents effect estimates (solid navy) of Excel Center graduation following Equation (5). Vertical solid navy bars represent the 95-percent confidence interval calculated using heteroskedasticity-robust standard errors.

Table 1: Baseline Characteristics

	Control Mean	Treatment Mean	Strata-Adjusted Difference (2) - (1)
	(1)	(2)	(3)
<i>Panel A: Student Characteristics</i>			
Male	0.297	0.256	-0.003 (0.012)
White	0.104	0.124	0.015 (0.023)
Black	0.209	0.231	0.029 (0.029)
Hispanic	0.644	0.610	-0.035 (0.032)
Age	28.103	28.819	0.266 (0.451)
Working Towards a Minimum Degree	0.624	0.701	0.053 (0.034)
Enrolled at AYW	0.102	0.136	0.019 (0.014)
Enrolled at Norwood	0.801	0.752	-0.000** (0.000)
Enrolled at South Austin	0.098	0.112	-0.019 (0.014)
<i>Panel B: Outcome Variables ($t=-5$ to $t=-1$)</i>			
Total Terms Enrolled	1.675	1.965	0.220+ (0.122)
Family Portal Logins	21.990	26.387	3.491 (2.926)
Credits Completed to Date	7.455	8.232	0.390 (0.427)
Credits Completed in Excel Center	2.127	2.697	0.296 (0.250)
Attempted Credits to Date	0.343	0.408	0.069 (0.052)
Alumni-Related Case Note Count	0.234	0.298	0.073 (0.053)
Attendance-Related Case Note Count	2.409	2.923	0.287 (0.375)
Life Coach Case Note Count	8.451	8.300	1.065+ (0.553)
Observations	492	403	

Notes: Student characteristic, enrollment, and course completion data provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. Variable outcomes are observed for each student before students are assigned to treatment. Panel A contains student characteristic variables that remain constant over time. Panel B contains outcome variables that potentially change over time. Panel B variables are observed over the five terms before treatment assignment ($t = -5$ to -1). Differences reported in column (3) adjust for randomization strata. Heteroskedasticity-robust standard errors are reported in parentheses.

**0.01, *0.05, +0.10 significance levels

Table 2: Nudging Case Notes by Treatment Assignment

	Control Group		Treatment Group	
	Any (1)	Number (2)	Any (3)	Number (4)
All Nudges	0.327	2.362	0.868	10.834
Benefits of Completing Program	0.138	0.337	0.625	2.538
Post Secondary Opportunities	0.098	0.203	0.427	1.067
Encouraging Persistence Throughout Term	0.173	0.827	0.772	3.491
Program Requirement Reminders	0.201	0.447	0.610	1.481
Other Communications	0.244	0.547	0.558	2.256

Notes: Case note data are provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. The first row of the table provides summary statistics of all nudges sent by life coaches to treated students 10 terms after a student is assigned treatment status. The next five rows break these nudging communications statistics into 5 mutually exclusive categories. Columns (1) and (3) report the rate at which students in the control and treatment groups, respectively, receive at least one nudge, while columns (2) and (4) report the average number of nudges control and treatment students, respectively, receive over the time period.

Table 3: Enrollment and Graduation Estimates

	Control Mean (1)	ITT Effect No Controls (2)	ITT Effect Controls (3)	IV Estimate (4)	Percent Change (5)
Terms Enrolled	4.240 (2.941)	0.077 (0.204)	0.018 (0.203)	0.034 (0.372)	1%
Enrolled or Graduated	0.319 (0.467)	0.063 ⁺ (0.033)	0.047 (0.030)	0.088 (0.054)	28%
Graduated	0.226 (0.418)	0.067* (0.030)	0.049 ⁺ (0.025)	0.093* (0.047)	41%
Terms Completing 1 or More Credits	2.209 (2.686)	0.294 (0.194)	0.213 (0.190)	0.401 (0.341)	18%
Randomization Strata FEs		X	X	X	
Individual Baseline Controls			X	X	
Observations	492	895	895	895	

Notes: Enrollment, graduation, and course record data provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. Data are restricted so that each student is observed for ten periods upon first being assigned to treatment. Outcomes in Table 3 are related to TEC Austin enrollment and graduation at the term level. A student is labeled as graduated if they complete TEC Austin within 10 terms of being assigned treatment status. Column (1) contains control group means for each variable. Estimates of Equation (1) are reported in column (2) and include randomization-stratum fixed effects but no baseline controls. Estimates of Equations (1) and (3) are reported in columns (3) and (4), respectively, and both include randomization-stratum fixed effects and individual baseline controls. Randomization strata are defined by term and campus during the 2020–21 academic year and by term, life coach, and gender during the 2021–22 academic year. Column (5) reports percent change in the respective outcome using the control-group mean and IV estimates in column (4). Cluster-robust standard errors at the randomization-strata level are reported in parentheses.

**0.01, *0.05, +0.10 significance levels

Table 4: Total Earned Credits Estimates

	Control Mean (1)	ITT Effect No Controls (2)	ITT Effect Controls (3)	IV Estimate (4)	Percent Change (5)
All credits	4.745 (5.350)	0.619 ⁺ (0.373)	0.262 (0.254)	0.493 (0.462)	10%
Core courses	2.236 (2.999)	0.366 ⁺ (0.208)	0.185 (0.153)	0.349 (0.283)	16%
Math	0.517 (0.807)	0.089 (0.057)	0.046 (0.043)	0.088 (0.081)	17%
English/Language Arts	0.676 (1.006)	0.135 ⁺ (0.069)	0.074 (0.054)	0.140 (0.098)	21%
Science	0.378 (0.557)	0.032 (0.039)	-0.002 (0.033)	-0.003 (0.061)	-1%
Social Studies	0.665 (0.869)	0.110 ⁺ (0.062)	0.066 (0.049)	0.124 (0.090)	19%
Other credits	2.510 (2.770)	0.253 (0.194)	0.077 (0.143)	0.145 (0.260)	6%
Randomization Strata FEs		X	X	X	
Individual Baseline Controls			X	X	
Observations	492	895	895	895	

Notes: Course record data provided by the Goodwill Austin Excel Center. The sample includes 895 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 403 assigned to the text treatment group and 492 assigned as controls. Data are restricted so that each student is observed for ten periods after first being assigned to treatment. Outcomes in Table 4 are related to cumulative credits earned at the GWA Excel center until the end of the tenth period after treatment-group assignment. Earned credits effects are reported by subject as well. Column (1) contains control group means for each variable. Estimates of Equation (??) are reported in column (2) and include randomization-stratum fixed effects but no baseline controls. Estimates of Equations (??) and (??) are reported in columns (3) and (4), respectively, and both include randomization-stratum fixed effects and individual baseline controls. Randomization strata are defined by term and campus during the 2020–21 academic year and by term, life coach, and gender during the 2021–22 academic year. Column (5) reports percent change in the respective outcome using the control-group mean and IV estimates in column (4). Cluster-robust standard errors at the randomization-strata level are reported in parentheses.

**0.01, *0.05, +0.10 significance levels

Table 5: Life Coach Details

	LC Text Dosage Stats		LC Experience Stats		
	# Initial LEO Texts Per Treated Student	Above Mean Text Dosage	# Pre-Treatment Students Advised	# Pre-Treatment Students Graduated	# Student In Sample Advised
Life Coach A	5.06	Yes	0	0	109
Life Coach B	4.26	Yes	231	37	111
Life Coach C	3.58	Yes	634	167	79
Life Coach D	3.44	Yes	0	0	95
Life Coach E	3.41	Yes	0	0	100
Life Coach F	3.40	Yes	244	63	22
Life Coach G	3.10	No	555	351	128
Life Coach H	2.93	No	513	107	86
Life Coach I	2.00	No	0	0	25
Life Coach J	1.05	No	358	92	124

Notes: Case note and life-coach student pairings data provided by The Goodwill Austin Excel Center. Life coaches are anonymized. The table details the average number of texts life coaches sent to treatment-group students in the first post-treatment term and life coach mentorship experience prior to the implementation of the text nudge. Two life coaches part of facilitating the nudge are removed from the data since they left TEC Austin at the start of the experiment. Records of the number of pre-treatment students life coaches advised are taken in the three years prior to the start of the experiment in September 2020.

Table 6: Treatment Effects by Life Coach Nudge Dosage and Experience Splits

	Life Coach Text-Nudge Dosage Split			Life Coach Experience Split		
	Below Median Nudge Dosage LC (1)	Above Median Nudge Dosage LC (2)	Difference (2)-(1) (3)	No Experience Life Coach (4)	Experienced Life Coach (5)	Difference (5)-(4) (6)
<i>Panel A: Graduation Outcomes</i>						
Graduated	0.045 (0.037) [0.217]	0.047 (0.034) [0.227]	0.002 (0.051) -	0.014 (0.041) [0.233]	0.067* (0.032) [0.216]	0.053 (0.053) -
<i>Panel B: LEO Comms Per Term Enrolled</i>						
All LEO Comms	1.434* (0.141) [0.371]	2.179* (0.116) [0.366]	0.744* (0.165) -	1.921* (0.140) [0.263]	1.847* (0.123) [0.445]	-0.073 (0.174) -
Completing Program LEO Comms	0.204* (0.033) [0.063]	0.796* (0.061) [0.038]	0.592* (0.067) -	0.665* (0.074) [0.030]	0.479* (0.046) [0.062]	-0.186* (0.073) -
Work in Term LEO Comms	0.465* (0.053) [0.154]	0.677* (0.041) [0.092]	0.211* (0.061) -	0.549* (0.051) [0.082]	0.612* (0.044) [0.145]	0.063 (0.063) -
Program Reqs. LEO Comms	0.272* (0.037) [0.077]	0.299* (0.025) [0.073]	0.027 (0.038) -	0.325* (0.029) [0.036]	0.263* (0.030) [0.103]	-0.062 (0.039) -
Post-Secondary LEO Comms	0.245* (0.032) [0.017]	0.152* (0.019) [0.040]	-0.093* (0.031) -	0.130* (0.022) [0.027]	0.228* (0.025) [0.032]	0.098* (0.032) -
<i>Panel C: Non-LEO Comms Per Term Enrolled</i>						
Non-LEO Comms	0.329 (0.356) [7.750]	-0.131 (0.299) [10.599]	-0.461 (0.467) -	-0.107 (0.400) [12.034]	0.214 (0.279) [7.475]	0.321 (0.484) -
Life Coach Comms	0.314 (0.324) [6.712]	0.219 (0.283) [9.336]	-0.095 (0.434) -	0.123 (0.382) [10.957]	0.370 (0.254) [6.236]	0.247 (0.447) -
Advisor Comms	0.036 (0.043) [0.294]	-0.021 (0.037) [0.336]	-0.058 (0.055) -	-0.067 (0.046) [0.331]	0.048 (0.036) [0.309]	0.115* (0.057) -
<i>Panel D: Skyward Logins Per Term Enrolled</i>						
Logins Per Term Enrolled	1.362 (1.691) [9.970]	1.893 (1.452) [10.605]	0.531 (2.046) -	-0.837 (1.182) [9.996]	3.328* (1.688) [10.583]	4.165* (2.103) -
Observations	363	516	879	329	550	879

Notes: Data are provided by the Goodwill Austin Excel Center. The table provides estimates of Equation (4), where the outcome is given in the left-most column. Columns (1) and (2) report the ITT effect for students assigned to below and above-mean nudge dose life coaches, respectively. The respective control-group mean is reported in square brackets. Column (3) reports the difference between columns (2) and (1). Columns (4) to (6) mirror that of (1) to (3), but where student assignment is split by life coach experience. Equation (4) controls for observable student characteristics and pre-treatment controls. Baseline covariates are allowed to have differential effects by LC type. Standard errors are clustered at the randomization-strata level, and are reported in parentheses for each estimate.

**0.01, *0.05, +0.10 significance levels

Table 7: Text Customization by Life Coach Experience

	Treatment Effect No Experience LC (1)	Treatment Effect Experienced LC (2)	Difference (2)-(1) (3)
Texts from Message Bank	1.230* (0.093)	0.900* (0.063)	-0.330* (0.099)
Text with Custom Message	0.482* (0.072)	0.817* (0.056)	0.334* (0.086)
Texts with Student Name	0.034* (0.013)	0.014* (0.005)	-0.020 ⁺ (0.012)
Texts with Link to Resources	0.243* (0.039)	0.234* (0.027)	-0.009 (0.041)
Texts Average Word Count	34.850* (2.756)	25.653* (1.907)	-9.198* (2.996)
Observations	329	550	879

Notes: Data are provided by the Goodwill Austin Excel Center. The sample includes 879 Excel Center students who were randomized into treatment between 9/2020 and 2/2022, 390 assigned to the text treatment group and 489 assigned as controls. Data are restricted so that each student is observed for ten periods upon first being assigned to treatment. Outcomes are related to the number of nudges treatment students received while enrolled at TEC meeting given customization criterion. Columns (1) and (2) provide treatment effect estimates for students assigned to inexperienced and experienced life coaches, respectively. Column (3) computes the differences between columns (2) and (1). Standard errors are clustered at the randomization-strata level and reported in parentheses.

**0.01, *0.05, +0.10 significance levels

A Appendix Figures and Tables

Table A-1: Additional Details on Randomization

	Control	Treatment	Number of	Treatment Probability		
	N	N	Strata	Min	Median	Max
	(1)	(2)	(3)	(4)	(5)	(6)
<i>2020–21 Academic Year (Stratified by Campus)</i>						
Term 1 (September)	17	33	3	0.60	0.66	0.70
Term 2 (October)	12	25	3	0.60	0.63	1.00
Term 3 (January)	11	27	3	0.67	0.68	1.00
Term 5 (April)	17	31	3	0.00	0.63	0.83
<i>2021–22 Academic Year (Stratified by Life Coach and Gender)</i>						
Term 2 (October)	296	199	16	0.31	0.38	0.64
Term 4 (February)	139	88	15	0.22	0.36	1.00

Notes: Data source is study information constructed by the research team.

B Text Message Bank

Messages were in a “mix and match” format that could increase the variety of messages students get. Each message could have any hook + direction, and could be customized by changing the wording or adding relevant detail where is helpful. Messages fell into one of four categories: (1) program completion, (2) staying on top of school work, (3) pursuing post-secondary school, and (4) completing program requirements.

Life coaches were given the freedom to expand the bank of potential questions. If there were other examples of hooks or directions that capture the same “key content” but weren’t listed here, they were instructed to add more messages to the list and expand the bank.

(1) Messages about completing the program

“Hook”	“Hook’s” key content	Direction/supplement	Supplement’s key content
A high school diploma can mean higher earnings after you graduate.	• HS diploma can = higher earnings later	Are you on track towards your goals? [Insert reference to resources here]	• Reflection for being on track • Helpful resources for that student’s progress
Your high school diploma can make it easier to get the job you want after you graduate.	• HS diploma can = more job opportunities	Are you on track to complete your program? [Insert reference to resources here]	
Your work at the Excel Center opens doors for further education like college.	• Graduating can = opportunities for post-secondary education	How is your progress towards graduation? [Insert relevant resources here]	

Example of “mix and match” & customization:

- *Hi [name], since we talked about jobs this week, I wanted to pass on that your diploma from the Excel Center will open up different job opportunities. Do you feel like you’re on track towards graduation?*

(2) Messages about work throughout term

“Hook”	“Hook’s” key content	Direction/supplement	Supplement’s key content
[This exam, e.g., Midterms] are on [date]. Are you ready?	• Reminder for upcoming assessments	Check out some of our favorite study tips at [this website]	• Helpful resource for studying & learning
Are you on track in your classes?	• Reflection for being on track in class	You can review class content at [this website/source].	
It’s easiest to remember and learn things from class if you do a little review each day.	• Consistent & repeated learning can = better retention of info	Have you heard about our individualized instruction, tutorial support, and mentoring? [insert relevant link]	
A little routine goes a long way.		Take 5 minutes to review your latest class.	• Non-intimidating task to get started
Better grades in class could mean automatic acceptance into college ([link about the Top 10% ruling])!	• High grades can translate to college opportunity	You can use [insert name of student portal] to check your grades and for any missing assignments.	• Reminder to check grades and assignments
Staying on track in class builds skills and knowledge for the job you want.	• Class work will be important for future work	Keep up the hard work--it’s paying off!	• Encouragement when they may want/need it, remembering past goals
Only [this many] weeks left in the term!	• Reminder of student progress, motivation to finish out the term	Take a minute to remember the goals that you created for yourself- you can power through!	
You’ve already finished [this many] weeks in the term!			
Your work this term is really impressive.			

Example of “mix and match” & customization:

- *Hi [name], just wanted to remind you that [this test] is on Thursday. Do you feel ready for this? There are study tips you can follow at [this link].*

(3) Messages about post-secondary school

"Hook"	"Hook's" key content		Direction/supplement	Supplement's key content
A 2 or 4-year degree can open even more doors than your diploma from the Excel Center.	• A post-secondary degree can = more opportunity (e.g., work/jobs)		Link to a list of local college websites & their list of programs	• Easy access to get familiar with college resources
Applications for college are opening now!	• Reminder about important deadline		Do you have everything you need for your next step?	• Prompts reflection about goals after the Excel Center, non-intimidating task to get started
The deadline to apply for student aid for the upcoming year is [date]			Take 5 minutes to consider what your next step could be!	
Many students are interested in college after they complete their time at the Excel Center.	• Considering college is common	+	Consider attending [this information session] on [date] to learn more about how it could work for you.	• Concrete next step in their progress to this goal/learning more
A 2 or 4-year degree after the Excel Center means higher earnings.	• A post-secondary degree can = higher income later on		Have you submitted the necessary materials?	• Reflection/level-set for their progress towards this goal
The Goodwill Career & Technical Academy (GCTA) provides accelerated training for professional career certifications in a variety of industries at little to NO cost to you.	• Opportunities available at the Excel Center • No cost			

Example of "mix and match" & customization:

- *Hi [name], a lot of students at the Excel Center want to go to college or other degree programs after they graduate. Would you be interested in discussing this sometime? In the meantime, here's a list of programs near here: [link]*

(4) Messages about staying on top of requirements

"Hook"	"Hook's" key content		Direction/supplement	Supplement's key content
It's time to [complete this step, requirement, form]!	• Reminder about important deadline		Visit [link] to complete this step now.	• Easy access/direction to complete what they need to
Do you have all of the credits needed for graduation?	• Reflection for being on track	+	Sign into the portal at [portal website] to check what your next steps are.	
			Send a message to your life coach if you have any questions!	• Reminding students they can rely on their life coach

Example of "mix and match" & customization:

- *Hi [name], have you submitted [this form] to register for next term? You can go to this link to complete this step in about 5 minutes: [link]*