Low-Touch Attempts to Improve Time Management among Traditional and Online College Students

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Abstract: We evaluate two low-cost college support programs designed to target poor time management, a common challenge among many undergraduates. We experimentally evaluate the programs across three distinct colleges, randomly assigning more than 9,000 students to construct a weekly schedule in an online planning module and to receive weekly study reminders or coach consultation via text message. Despite high participation and engagement, and treated students at two sites marginally increasing study time, we estimate precise null effects on student credit accumulation, course grades, and retention at each site for the full sample and for multiple subgroups. The results and other supplemental evidence suggest that low-touch programs that offer scheduling assistance, encouragement, and reminders for studying lack the required scope to significantly affect academic outcomes.

1. Introduction

Approximately half of all students who enroll in college never complete their program and students who do complete often struggle, developing limited skills along the way (Arum and Roksa 2011). Student effort is a key determinant of academic outcomes, and many students devote little time to regular studying (Babcock and Marks 2011). Despite a clear positive association between study time and academic outcomes (Brint and Cantwell 2010; Stinebrickner and Stinebrickner 2004, 2008), underachieving students in both traditional and online colleges often manage their time poorly and study only a few hours each week (Dohetry 2006; Beattie, Laliberté, and Oreopoulos 2018; Beattie, Laliberté, Michaud-Leclerc, and Oreopoulos 2019).

To help students improve their time management and increase weekly study time, we designed and tested two low-touch interventions across three different college campuses. Our sample includes over 2,000 undergraduate students at the St. George Campus at the University of Toronto (UTSG), one of the highest ranked public institutions in North America, approximately 1,500 students from the University of Toronto's satellite campus in Mississauga (UTM), a less-selective commuter campus, and a sample of over 6,000 undergraduate students at Western Governors University (WGU), an online-only college. Students at all three experimental sites study little and manage their time poorly. Struggling students at the University of Toronto (UofT) procrastinate, acknowledge poor time management as the biggest challenge to their academic success and, despite an abundance of room in their schedules,[1] do not increase their planned study times after experiencing poor performance (Beattie, Laliberte, and Oreopoulos 2018; Beattie,

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[1] We show in Section 3 that after accounting for weekly hours of paid work, commuting time to and from campus, time spent attending lectures, and time spent sleeping, the median student has more than 90 hours per week available but only devotes 12 hours to studying outside the classroom. The bottom 25 percent of students study less than 5 hours per week.

Laliberte, Michaud-Leclerc, and Oreopoulos 2019). Likewise, students at WGU access their online course materials quite infrequently,[2] and online education is generally a setting where time management issues are particularly likely to drive poor performance because of the asynchronous, unstructured nature of online courses.[3]

Across all three locations, students randomly assigned to the treatment group receive information about the benefits of sufficient study time and complete an online planning module in which they make a calendar describing their planned weekly commitments in the upcoming year, including the times during the week they plan to study. To keep these plans salient, we encouraged students at the UofT campuses to provide their phone numbers and students at WGU to download the WGU mobile application so that we could send students reminders about their scheduled study times via text message throughout the academic year. We assigned students in the control group at the UofT campuses to a personality test, while students in the control group at WGU only completed the standard online student orientation without accessing the planning module.

Our planning interventions are designed to improve time management and increase study time through four channels. First, many individuals tend to underestimate the time required to complete a task (Kahneman and Tversky 1979), with more complicated tasks, such as navigating university courses, usually associated with greater underestimation (Buehler et al. 1994). Decomposing a task into smaller segments, however, helps individuals form more accurate estimates about the time required to complete it (Buehler et al. 1994; Forsyth and Burt 2008). Our planning intervention guides students through unpacking their weekly study schedules into smaller

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[2] The average student logs into to their portal only 2.1 days per week. In addition, 90 percent of students log in less than 3.7 days per week and 18.5 percent of students log in less than 1 day per week

[3] Indeed, recent experimental and quasi-experimental evidence finds that students in online courses perform worse than students in traditional classroom settings (Bettinger et al., forthcoming; Figlio et al. 2013)

study sessions that are dispersed throughout the week, while considering their weekly time commitments outside of school. Second, the planning intervention is also designed to increase 'implementation intentions,' a term that refers to the process of identifying when, where, and how one will fulfil a plan (Gollwitzer 1993). Recent experimental evidence suggests that fostering implementation intentions can increase desired behavior across many domains, including exercise, diet, recycling, project completion, and voting (Gollwitzer and Sheeran 2006; Nickerson and Rogers 2010). By requiring students to define implementation intentions at the beginning of the academic year, our planning intervention helps them establish clear study goals to follow while working through their courses.

Third, the periodic text-message reminders that students receive about their planned study times help keep their goals salient throughout the academic year. The use of follow-up reminders is motivated by economic models of limited memory and inattention (Mullainathan 2002; Ericson 2014; Karlan et al. 2010), which predict that individuals are susceptible to inattention to their prior plans, thereby causing delays or even failures in plan completion. Reminders have been shown to successfully increase plan completion in a variety of domains, including exercise (Calzolari and Nardotto 2012), repayment of loans (Cadena and Schoar 2011), savings accounts deposits (Karlan et al. 2010), and college matriculation (Castleman and Page 2015).

Fourth, the text messages students received at the UofT campuses came from a senior-undergraduate student coach, whose job was to inquire once a week about how students were progressing and offer encouragement. Coaching or advising done over the phone or in person has proven effective in improving students' academic outcomes at both two-year and four-year colleges (Scrivener and Weiss 2013; Bettinger and Baker 2014; Oreopoulos and Petronijevic 2018). Although there is less evidence on the effectiveness of personal coaching that occurs via

text message,[4] we offered treated students a text-message coaching program to help them address any individual-specific challenges to following through with their plans.

Despite our time-management programs being well-received, generating a high degree of student engagement,[5] and causing an increase in self-reported study time at both UofT campuses of nearly 2 hours per week, we find no impact on academic outcomes across all three experimental sites (the two campuses of UofT and WGU). Specifically, we estimate no treatment effect on credit accumulation or course grades at UTSG and UTM and no treatment effect on student credit accumulation or retention at WGU. We reconcile these results by noting a relatively weak association between study hours and grades. Our estimated effect on study time of nearly 2 hours a week may be too small for us to detect corresponding grade effects. These results hold even after investigating potentially heterogeneous treatment effects across several student subgroups.[6]

It is likely that a more comprehensive program is required to generate larger change in behavior and outcomes. Despite studying more than control students, treated students fell drastically short of the new study goals they set in their calendars, suggesting that many suffer procrastination tendencies that our intervention was unable to alleviate. If present-biased preferences keep students from following through with their plans (Laibson, 1997; O'Donoghue and Rabin, 1999), improving the quality of students' plans and sending light-touch reminders about their plans may

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[4] Oreopoulos, Petronijevic, Logel, and Beattie (2018) show that while personal coaching via text message did not improve academic outcomes in a sample of students at UofT, it did significantly and positively impact non-academic outcomes, such as student mental health and feelings of belonging at the university.

[5] We show in Section 5 that treated students engaged with the calendar exercise, had high response rates to the weekly text messages from their coaches, and wanted the program to continue.

[6] The experiments at WGU and at UofT were both pre-registered with the AEA RCT Registry. The RCT IDs are AEARCTR-0000972 and AEARCTR-0000810 at WGU and UofT, respectively. Our analysis of treatments effects in the full sample and across student subgroups closely follows our pre-registered analysis plans.

not be enough to affect academic outcomes.[7] Indeed, a more comprehensive intervention with regular contact and guidance may be required.

We also use our unique survey data at the UofT to show that, in addition to studying more than low performers, top-performing students have much higher incoming high school grades, set higher expectations for themselves, are more likely to finish what they start, manage their time well, and plan well into the future, and are less likely to study at the last minute and delay starting assignments. These important differences among high- and low-performing students, coupled with the large study effort increase that is required to generate significant change in outcomes, imply that a more comprehensive and intensive intervention – designed to affect many dimensions of student behavior – is likely required to generate meaningful change in academic outcomes.

Our study contributes to a broad and growing literature on the application of behavioral insights to education settings (Lavecchia, Liu, and Oreopoulos 2016; Damgaard and Nielsen 2018). Recent attempts to help improve academic achievement focus on offering assistance with college and financial aid applications (Bettinger et al. 2012; Castleman and Page 2015; Castleman and Page 2016), prompting students to think about future goals (Clark et al. 2017; Dobronyi et al. 2017), encouraging healthy perspectives for dealing with setbacks or anxiety (Yeager et al. 2016; Bettinger et al. 2018), and offering low-cost encouragement or advising (Fryer 2016; Castleman and Meyer 2016; Oreopoulos and Petronijevic 2018). A collective pattern emerging from these

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[7] Students may also be overconfident, as Twenge et al. (2012) find that most college students believe they have above average abilities. If students overestimate their abilities, they may make insufficient study plans and underestimate the penalties they will face from failing to follow-through on their plans (Dunlosky and Rawson, 2012). It is also possible that students have low expectations on the returns to studying on grades, or the returns to grades on longer term outcomes, as the benefits to studying are long-term, uncertain, and highly ambiguous. Better motivating the benefits to studying or reducing ambiguity (Epstein and Halevy, 2018) may therefore be a channel through which future interventions can attempt to increase study effort.

studies is that interventions that nudge students toward taking relatively simple, one-time actions are more effective than interventions that target changing longer-term habits or routines.[8]

We focus specifically on helping students improve time management skills and increase overall study time, treating study effort as a necessary condition for academic success, as poorly-performing students who study less than 10 hours a week are unlikely to benefit from any intervention that does not increase this variable. Our finding that helping students create clear schedules and offering reminders increases study time suggests it is possible to moderately affect persistent academic behavior with low-cost scalable interventions in higher education. The absence of effects on grades and credit accumulation, however, is informative for higher-education policymakers considering the efficacy of programs that emphasize the importance of time management and study effort. [9]

The remainder of this paper is organized as follows: The next section provides a detailed description of our intervention and its implementation at the UofT campuses and WGU. Section 3 describes the experimental data from both experiments and outlines our empirical strategy for estimating the treatment effects, while Section 4 presents the results. We discus and interpret our results in Section 5 and Section 6 provides concluding remarks.

2. Description of Intervention

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[8] There are exceptions that find positive effects of low-cost interventions on sustained changes in behavior. For example, Chande et al. (2015) find that text message prompts increase attendance in adult education programs and Patterson (2018) finds that commitment devices increase study time and improve performance in a Massive Open Online Course.

[9] Our findings here contribute to the broader literature on planning interventions that shows encouraging people to make a concrete plan for action has shown promise in settings with a single action such as voting (Nickerson and Rogers, 2010) and getting the flu vaccine (Milkman et al., 2016), but has not shown to be effective in increasing sustained actions, such as attending the gym (Carrera et al., 2018).

In this section, we describe the implementation of the experiments at both UofT and WGU, providing greater detail about the planning interventions and the follow-up messages students received.

2.1. The Intervention at UofT

We conducted our experiment at UofT throughout the 2017-18 academic year. At both the main campus, UTSG, and the satellite campus, UTM, we partnered with all first-year economics instructors to include a 45 to 60 minute 'warm-up' exercise at the beginning of the course worth 2 percent of students' final grades. The exercise had to be completed within the first two weeks of the fall semester for students to receive course credit, with the type of exercise each student completed depending on whether he or she was randomly assigned to the treatment or control group. All students logged in using their university accounts and completed a brief introductory survey, in which they provided information about their parental education, their own expected educational attainment, their work plans, their educational history, and their self-reported tendency to procrastinate or become distracted. Students assigned to the treatment group were then required to complete an online module that first taught them about the importance of sufficient study time and then guided them through a planning intervention, while students assigned to the control group were given a personality test. Below we describe the treatment and control modules in more detail.

2.1.1. Planning Intervention

All students randomly assigned to the planning intervention at UofT completed a three-part online module. We offer an overview of the module in this subsection and provide full documentation in Appendix B.

During the first part of the planning module, we presented the college's recommendation for weekly study time (at least 4 to 6 hours per course, or at least 20 to 30 hours per week for a full course load) and information on the importance of sufficient study time for academic performance and general life satisfaction. We motivated the latter by showing descriptive evidence (gathered from previous experiments we ran at UofT) about the positive associations between study time and grades and study time and measures of mental health. In the second part of the module, we asked students to read testimonials from former students, each of which described a common challenge faced by university students and how making a schedule and studying regularly can help students avoid these pitfalls. After reading through the stories, students wrote about how they could motivate themselves to stick to a regular study routine and identified the study strategies they thought would be the most helpful for doing so. Students were encouraged to slow down or write a little more if they tried to continue through the exercise below a minimum time or word-count restriction. After this writing exercise, students were asked to set a personal target for weekly study hours.

Having discussed the importance of keeping an organized schedule and studying enough, the third part of the online module asked students to make their own weekly schedule by building a weekly calendar. We first asked students to populate their calendars with class times, which they could do by downloading a standard electronic calendar (ICS) file from their university platform and then uploading the ICS file to our platform. Students then scheduled their anticipated job schedules along with their regular sleep routines. Once they had accounted for items with little scheduling flexibility, students were asked to populate their calendars with weekly study times. The module asked them to reconsider the importance of sufficient and regular study time and would not allow them to proceed unless the number of scheduled study hours throughout the week

matched their personal target for study hours. As the final step toward completing their calendars, students scheduled personal time for seeing friends and family and engaging in other activities they enjoy.

To help students stay on track throughout the academic year, we made their weekly calendars available to them. If students already had a Gmail account, they simply had to provide their Gmail address and we then uploaded their calendars directly into their Google calendars. If students did not have a Gmail account, we gave them the option to create one or to simply download their calendar as an ICS file and upload it to whichever calendar application they prefer to use.[10]

For the last step of the exercise, all students were encouraged to enroll in a virtual coaching program called *You@UofT*.[11] We explained that students would be matched with an experienced, senior-undergraduate coach whose job would be to check-in once a week via text message to inquire about how students were doing with their study goals, offer support and encouragement, and answer any questions. Across both campuses, 80 percent of students opted-in to the coaching program by providing their cell phone numbers.

Our coaches were hired through a research opportunity program, which allows students to participate in a research project for course credit (rather than pay). Coaches were solicited to apply for the program through various student service offices and we sought recommendations for keen, talented senior undergraduates who had prior experience helping new students (as, for example, residence dons, orientation volunteers, or tutors). Upon joining the team, coaches reported to our

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[10] A total of 1,685 students completed the planning intervention at UofT and 1,424 (84.5 percent) provided a Gmail address for us to upload their calendars directly into their Google calendars. The remaining students downloaded their calendar from our platform as ICS file.

[11] As in Oreopoulos and Petronijevic (2018), we chose the name to emphasize that the program would help coach students toward their individual definitions of success.

program manager, a graduate student in economics, who communicated best practices and ensured proper protocol was being followed.

Once students opted-in to the coaching program, they were assigned to a specific coach and each coach was assigned a few time slots during the week to be the coach who was on call. During each on-call time for a given coach, we sent a batch message to all students who were assigned to that coach to spur productive conversation. If students replied while their coach was still on call, that coach would continue the conversation. If students replied after their coach's shift ended, the coach who was currently on call or the team manager was responsible for closing the conversation.

The batch messages we sent to students fell into two general categories. The first message type consisted of a weekly study tip on how to use study time effectively. When sending these messages, we took advantage of knowing when students planned to study from the calendars they completed, sending the messages 15 minutes prior to one randomly selected study session. The second type of message was a weekly check-in from the students' coaches, which was designed mostly to offer support and inquire about how well students were managing their time. To help effectively close conversations, we sent an automatic follow-up message with a tip or encouragement if the student did not respond to the original check-in message. A list of example check-in text messages that we sent throughout the academic year is available in Table C1 in Appendix C.

Student engagement with the *You@UofT* text-messaging program was quite high, with 26 to 66 percent of treated students responding to our messages each week. In terms of cumulative engagement, 80 percent of treated students sent at least one text message back to their coach during

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the academic year. We also asked students via text message for feedback on our coaching program, and many expressed gratitude and appreciation for the study tips and support.[12]

2.1.2. Personality Test

As in Oreopoulos and Petronijevic (2018), students who were assigned to the control group at both UTSG and UTM were given a personality test measuring the Big Five personality traits of agreeableness, conscientiousness, extraversion, openness to experience, and emotional stability. The test tended to take about 45 to 60 minutes to complete, and students were emailed a report describing their scores on each trait upon completion of the exercise. Beattie, Laliberté, and Oreopoulos (2018) describe the personality test in greater detail in the appendix of their paper and use the resulting data to explore non-academic predictors of performance in university.

2.2. The Intervention at WGU

In this subsection, we provide an overview of the planning module students completed at WGU. Full documentation is presented in Appendix B.

WGU is a large non-profit online college in the United States.[13] Prior to the beginning of his or her first semester, each new student participates in an online student orientation. As part of our experiment, randomly-selected undergraduate students who enrolled between January 2 and March 1 of 2017 were additionally required to complete a two-part planning module at the end of

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[12] An anonymized list of student response to our feedback request and more detailed information on student engagement with the text-messaging program are available upon request.
[13] See Appendix A for a broad overview of WGU.

the online orientation.[14] The planning module was similar to that which was completed by students at UofT.

In the first part, we again shared the college's recommendation for weekly study time (1-2 hours per "competency unit"/credit or 3-6 hours per typical course)[15] and required students to complete an interactive weekly planning activity, in which they allocated their time among four categories (work, study, recreation, family and home) and 21 subcategories.[16] Upon completion of the planning exercise, the second part of the module asked students to organize the college-assigned Google calendar associated with their WGU email account. This calendar was pre-populated with categorical events from each of the four primary activity types and students were required to organize the calendar to match their planning activity allocation. When students finished organizing their calendars, they submitted a screenshot of their completed calendar as an enrollment requirement.

With each student having a completed calendar in hand, WGU recreated study events onto treated students' calendars each week for the remainder of the semester. Students were able to modify their study schedules at any time, with study events being visible on students' Google calendars, the calendar in the WGU student web portal, and the WGU mobile application. The 81.8 percent of students who installed the WGU mobile application also received mobile notifications 15 minutes prior to two randomly selected study sessions between 9am and 8pm each

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[14] Students in the control group only completed the regular online orientation.

[15] Among students taking 5 courses, this recommendation amounts to 15 to 30 hours per week of total study time, which is very similar to the recommendation at UofT of 20 to 30 hours.

[16] **Work-** working, commuting, and other work time; **study--**mentor support, course readings, course writing, group activity, and other study time; **recreation-**watching tv, socializing, reading, exercise and sports, browsing the internet, and other recreation; and **family and home-**caring for family, preparing and eating meals, cleaning and laundry, household management, lawn and garden, sleep, and other home and family.

week. Additionally, all treated students received study notifications in the WGU web portal "notification center."

To help students unpack their semester schedules, we also populated their calendar with multiple unique "completion benchmarks" that were customized for each course. WGU students digitally meet with a counselor to set their course schedules prior to the beginning of each semester. In this meeting, they outline the anticipated start and end dates for each course. Nearly all courses at WGU have a "Course of Study Guide" or syllabus that divides the course into 4-8 segments or blocks. We combined students' anticipated start and end dates with their course syllabi segments to create evenly spaced intermediate completion benchmarks for each course in which a student is enrolled. These benchmarks were populated in students' WGU Google calendars and automatically adjusted to any changes made by WGU or the students to the scheduled start or end date in WGU's system. Students could view these benchmarks in the Google calendar, WGU web portal, and WGU mobile app, and students with the mobile application received a reminder at 4pm two days before each completion benchmark, reminding them that they would need to complete their benchmark task in the next two days to stay on track.[17] Examples of the benchmark reminders can be found in Table C2 in Appendix C.

3. Data, Motivating Evidence, and Empirical Strategy

In this section, we describe the data we collected from UTSG, UTM, and WGU, along with our strategy for estimating treatment effects across the three sites.

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[17] These completion benchmark notifications were also displayed on all WGU student's web portals.

3.1. Experimental Randomization and Sample Description at UofT

We begin the description of the data at UofT with Table 1, which reports the total number of students in the treatment and control groups, as well as the fractions of students sorted to treatment and control at each campus. Prior to the experiment, we intended to sort one third of students to both the treatment and control groups at UTSG[18] and to evenly divide students across treatment and control groups at UTM. Table 1 shows that slightly more than one third of students (35.8 percent) were sorted to the treatment group and slightly less than one third (30.4 percent) were sorted to the control group at UTSG, while we reached our target fractions at UTM, as the percentages of students sorted to treatment and control are not statistically different than 50 percent. Across both campuses, we have 3,581 students in our study, with 2,044 coming from UTSG and 1,537 coming from UTM. The completion rates for the online modules are very high across both campuses, ranging between 97 and 98 percent. We can match 94 percent of our experimental sample to the university's administrative data on course grades, leaving us with an analysis sample of 3,344 students.[19]

Tables 2 and 3 present balancing tests UTSG and UTM, respectively, showing that the treatment and control group are balanced along observable characteristics. The lone exception (out of 32 tests for mean differences) is that students in the treatment group at UTM report being slightly more likely to often think about their futures. We demonstrate below that our treatment effect estimates are robust to controlling for this variable and many other covariates.

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[18] The remaining one third of students was sorted to a different treatment group, which is the subject of a separate, standalone paper.

[19] The university's grades data only include students who are registered at the end of September in the fall semester of 2017, which is why we are unable to match a small fraction of students who are no longer registered at that time. The match rate to the grades data is not differential by treatment status.

In terms of the sample characteristics, approximately half our sample at the UofT campuses is male, the average student is 18 years old, approximately 40 percent of students speak English as their first language, 50 percent of students are international, and approximately 75 percent are in their first year of studies. These characteristics are similar across UTSG and UTM. Differences start to emerge, however, when one considers variables related to academic preparedness. The average incoming high school grade average at UTSG is 91 percent, while it is 85 percent at UTM, reflecting the differences in selectivity across the two campuses. The 75th percentile student at UTM has a high school grade average of 88 percent, which corresponds to the 25th percentile student at UTSG. Also consistent with differences in selection criteria, many students at both campuses intend to earn at least an A- grade average and more than a bachelor's degree, but the factions are higher at UTSG (74 percent and 48 percent) than at UTM (62 percent and 40 percent). It is also the case that only 23 percent of the UTSG sample consists of first-generation students, while the fraction is considerably higher at UTM, at 34 percent.

With respect to student time commitments, the average student at UTSG expects to study approximately 18.6 hours per week in university, work approximately 6.4 hours a week for pay and spends approximately 24 minutes commuting to campus (in one direction). At UTM, students expect to study 15.6 hours per week, work 8.2 hours for pay and spend 31 minutes commuting to campus.[20] On average, students at UTSG and UTM report spending 13.6 and 11.8 hours per week, respectively, studying outside of class in high school. In subsection 3.3, we provide descriptive evidence on student study times during the fall semester at UTSG and UTM, along with the associations between study time and academic performance.

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[20] Note that the expected study time per week is collected during the baseline (pre-randomization) survey for both treatment and control group students. This variable differs from the actual (self-reported) study time, which appears in Figure 1 and is gathered during the follow-up survey at the end of the semester.

3.2. Experimental Randomization and Sample Description at WGU

At WGU, our study sample includes 6,065 undergraduate students who enrolled between January 2 and March 1 of 2017. Students were randomly assigned to either the treatment or control group based on the last two digits of their sequentially assigned student number. Table 4 shows the balance of observable characteristics across treatment and control, indicating that the groups are mostly balanced in terms of observable characteristics. Among the 16 characteristics presented in the table, four are statistically different across treatment and control groups. Students in the treatment group are approximately half a year older, 2 percentage points more likely to work full time, 2 percentage points more likely to have annual incomes between $45,000 and $65,000, and 2 percentage points more likely to be first-generation students. While there are more statistically significant differences than one would expect from random assignment, we are able to verify that the treatment assignment mechanism was followed in over 99.9% cases.[21] Furthermore, these differences are not economically large, and we show below that controlling for these variables (and many other covariates) does not affect our estimated treatment effects. Finally, our experimental design also involved randomly assigning graduate students to the planning treatment.[22] While our analysis plan specified that these graduate students be dropped from our analysis, we show in Appendix D that our sample balances across observable characteristics (1/16 variables differ at the 5% level) when graduate students are included and that our results remain unchanged.

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[21] Based on the last two digits of student's id numbers, only 4/6065 are assigned to a treatment group that does not correspond to the assignment rule. Our estimates are robust to exclusion of these observations.

[22] Graduate students assigned to the treatment were not sent benchmark reminders in all courses, but were otherwise treated identically to undergraduate students.

In terms of the sample characteristics, approximately 34 percent of the WGU students in our study are male and the average student is 35 years old – a marked difference from the UofT sample, where half of the sample is male, and the average student is only 18 years old. Nearly 80 percent of the sample consists of white students, while Hispanic and black students each comprise approximately 11 percent of the sample. A large majority (75 percent) of students are employed full time and many (40 percent) have annual incomes of $65,000 or more.[23] Approximately 42 percent are first-generation students whose parents did not complete post-secondary education.

3.3. Descriptive Facts on Student Study Time at UofT and WGU

Figure 1 plots the distribution of time that students have available and the distribution of time they self-report studying during a regular week in the fall semester, using information from baseline and follow-up surveys among students from our two UofT campuses. Many students at UofT study far less than the time they have available to do so, with the median student reporting that they studied only 12 hours per week in the fall semester despite having more than 90 hours available, while the bottom quarter of students report studying less than 5 hours per week.

We construct time available in Figure 1 using the information students provide in our baseline survey about their expectations for upcoming weekly hours of work (for pay), commuting time to and from campus each week, time spent attending lectures each week, and time spent sleeping.[24] We gathered information on actual (self-reported) study time during the fall semester by

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[23] One may be concerned that students who work full time do not have available time to increase study intensity. In our analysis of heterogeneous treatment effects below, we show that our estimates do not differ across WGU students by employment status or household income.

[24] We acknowledge that there are other demands on students' time that are not captured by these variables, such as eating, sports and clubs, self-care, church going, etc. To make sure that we are not drastically overstating the time students have available, we have also done calculations where we conservatively assume that students only have 60 hours per week for being productive in school. Taking 60 hours per week as the total available time and subtracting time spent working (for pay), commuting, and attending class, the median student still has 41 hours remaining and 90 percent of students have at least 27 hours per week remaining.

conducting a follow-up survey with students at the end of the fall semester, asking how many hours they spend studying outside of class during an average week (which is the reported study time variable in Figure 1) and how many hours they spend studying during a week in which they are preparing for midterms or exams.[25] Because the follow-up survey did not have grade incentives attached, the aggregate response rate was only 48 percent, with 47 percent of students responding at UTSG and 50 percent of students responding at UTM. However, attrition from the follow-up survey was not differential by treatment status at either campus and all covariates remain balanced across treatment and control groups in the subsample of students who completed the follow-up survey.

In Figure 2, we quantify the amount of available time students at UofT are not using toward studying by subtracting reported study time from available time and plotting the resulting distribution of remaining time.[26] The vertical lines in the figure represent the 25th, 50th, and 75th percentiles, respectively, indicating that three-quarters of students expect to forgo at least 65 hours per week in potential study time, 50 percent of students expect to forgo at least 78 hours, and one-quarter of students expect to forgo more than 87 hours a week. We note again that these calculations already account for sleeping time, class time, and self-reported expectations for time required for working and commuting to and from school each week.[27]

Table 5 presents summary statistics for self-reported student study time at UTSG and UTM in the fall semester during a typical week and during a week spent preparing for midterms or exams.

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[25] The sample in Figure 1 is restricted to students in the control groups across both campuses of UofT.
[26] We construct this figure by restricting the sample to students in the control group and pooling together students at UTSG and UTM.
[27] Using the more conservative calculation that assumes students only have 60 hours per week for being productive in school (see footnote 19), the median student expects to forgo 26 hours per week and 75 percent of students expect to forgo at least 14 hours per week.

Across both campuses, the average student in the control group reports having spent only 15.6 hours outside of class studying during average week in the fall semester.[28] During a week of preparing for midterms or exams, students report studying 24.8 hours, on average – an increase of nearly 10 hours from a typical week but still only marginally more than the number of hours one typically spends at a part-time job. In terms of the breakdown across campuses, students at UTSG study more than those at UTM: the average student at UTSG reports studying 16.8 hours, on average, during a regular week and 28.1 hours during a week before exams, while the average student at UTM reports studying 14 hours during a regular week and 20.1 hours before exams.

The survey evidence implies that students at UTSG and UTM study relatively little, which raises the question of whether students could meaningfully improve academic outcomes by increasing study time. In Figure 3, we pool the control groups across both campuses and plot descriptive associations between self-reported hours spent studying during a typical week in the fall semester and the average grade across all courses taken in that semester, the GPA earned across all courses, and the number of credits earned. We also plot the associated linear relationships, estimated on the underlying student-level with regressions that include campus fixed effects. The estimated coefficients from these regressions are reported in columns (1) and (3) of Panel A in Table 6.

All relationships are positive and statistically significant, implying that an increase in weekly study time of one standard deviation (13 hours) is associated with an increase in average course grades of 11.5 percent of a standard deviation, an increase in GPA of 13.6 percent of a standard deviation, and increase in credits earned of 11 percent of a standard deviation. These relatively

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[28] We focus only on students in the control group in this subsection, deferring an exploration of whether treatment significantly increased student study time to Section 4.

small magnitudes are likely biased downward by measurement error in study time attenuating the relationships, as student study time is self-reported retrospectively. To mitigate the attenuation bias, we instrument for weekly study time using the following variables from the baseline survey: study hours per week in high school, self-reported expected study hours per week this semester, tendency to regularly "cram" for exams, expected hours per week working for pay during the semester, and expected commuting time to campus. The IV estimates, reported in columns (2) and (4) in Table 6, are appreciably larger than the OLS estimates, indicating that a one standard deviation increase in study time is associated with an increase in mean grades and GPA in the fall semester of 22 and 21 percent of a standard deviation, respectively. [29]

In Panel (B) of Table 6, we focus only on the relationship between weekly study time and grades in math or economics courses. We do so to address concerns about grade inflation attenuating the relationship between study time and course grades, relying on the notion that grading in math and economics courses is likely to be more objective than in other social science or humanities courses, resulting in a tighter link between student effort and outcomes. This is indeed what we find, as the IV estimates indicate that a one standard-deviation increase in weekly study time is associated with an increase in the mean math and economics grade of 37 percent and

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[29]Brint and Cantwell (2008) also use retrospectively self-reported study time from the University of California Undergraduate Experience Survey to show that a one standard-deviation increase in weekly study time is associated with an increase in GPA of 10 percent of a standard deviation, an estimate that is very close to our OLS estiamte. Accounting for measurement error in retrospective self-reports, Stinebrickner and Stinebrickner (2004) use time-diary data collected at six different times during the academic year at Berea College to estimate that a one standard-deviation increase in daily study time is associated with a 0.43 standard deviation higher college GPA. The authors also find evidence of non-linear effects on study time on grades, where the effect of study time is diminishing. We tested for non-linear effects by adding a quadratic study time term in each of the specifications in Figure 3, but the quadratic terms were not significant in any specification. To compare the estimates from Stinebrickner and Stinebrickner's daily study time data with those from our weekly data, note that the standard deviation of daily study time in their data is 1.62 hours per day (or 11.34 hours per week) and the standard deviation of GPA is 0.686 points. In our data at UofT, the standard deviation of study time is 13 hours per week and the standard deviation of GPA is approximately 1 point.

30 percent of a standard deviation, respectively.[30] Taken together, the descriptive relationships that adjust for measurement error indicate that an additional 10 hours of studying per week is associated with an increase in mean grades between 2.2 and 4.6 percentage points. Although these estimates do not reflect a causal relationship, the descriptive relationship between studying and grades is small when comparing only marginal differences in studying. Large differences – more than 10 hours a week – are needed, all else equal, to observe changes in letter grades (i.e., moving from a B grade to an A grade). We return to this point in Section 5 below, where we interpret our treatment effects.

Turning to the relationship between study intensity and student outcomes at WGU, we note that we are unable to directly observe the frequency and duration of study time because course content is hosted on third-party platforms. However, students are able to access all of their courses through the WGU portal and we observe how frequently students visit this portal. Although these data do have limitations, they provide a measure of engagement that does not suffer from problems related to retrospective self-reporting.

The data suggest that students taking courses online with WGU study infrequently. Figure 4 shows the distribution of the number of days per week that students log into WGU's online portal. The average student logs into the WGU portal 2.1 days per week. In addition, 90 percent of students log in less than 3.7 days per week and 18.5 percent of students log in less than 1 day per week. While it is possible that students are not always accessing course material via the WGU website, the log-in data indicate that many students access materials on WGU's portal quite infrequently. In Figure 5, we plot the correlation between days logged in per week and credits

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[30] These estimates may understate the relationship between studying and performance in math and economics, as some of the weekly study time is likely devoted to courses other than math and economics.

earned. We find a strong and statistically significant positive relationship between log in activity and credits earned, with a one standard deviation increase in days logged in per week (1.3 days) correlating with a 51.3 percent of a standard deviation increase in credits earned.

The descriptive evidence implies that many students at all three experimental sites study quite little, with large slack for increasing study intensity but potentially low returns from doing so. We explore whether our planning intervention was effective at increasing student study time and academic outcomes in Section 4 and discuss and interpret our results in Section 5.

3.4. Empirical Strategy for Estimating Treatment Effects

Having successfully randomized students across treatment and control groups at UTSG, UTM, and WGU, we estimate the effects of the planning treatment with a comparison of mean outcomes in a simple regression framework. The main specification, which we estimate separately at each site, is given by

$$y_i = \beta_0 + \beta_1 Treatment_i + \rho' X_i + u_i. \tag{1}$$

Here, the outcome of student is regressed on an indicator for the student being assigned to the treatment and, in some specifications, additional student-level control variables. In specifications that pool students from UTSG and UTM, we include campus fixed effects.

The main parameter of interest is β_1, the estimated effect of the planning treatment. This parameter represents an Intent-to-Treat effect, as students are included in the treatment group regardless of whether they completed the online exercise, took it seriously, provided their phone number, responded to a coach, or used their weekly calendar. Given that our completion rates and

opt-in rate are quite high, these estimates are likely close to the average treatment effect of completing the exercise.[31]

With respect to outcomes, at UofT, our main outcomes of interest are course grades,[32] overall grade point average (GPA), the number of credits attempted, the number of credits earned, and persistence into second semester. At WGU, our main outcomes of interest are the number of credits attempted, the number of credits earned, the number of days until a student completed his or her first credit, and retention.[33] When the outcome of interest is course grades, we stack all course grades and run a regression at the student-course level, clustering standard errors at the student level. The effects on all other outcomes are estimated with regressions at the student level and robust standard errors are reported.

4. Results

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[31] Recall that 97 percent of students completed the online exercise at the UofT campuses. In addition, 80 percent of students who were invited to participate in the text-messaging program provided a phone number. All students who were assigned to the treatment group at WGU were required to complete the planning module and submit a screenshot of their study calendar as a condition of enrollment. The enrollment module at WGU does not allow students in the treatment group to advance until they have completed these steps.

[32] One may worry that a practice of "grading on a curve" at UofT could attenuate measured treatment effects on course grades. We note, however, that while the Faculty of Arts and Science at UofT (to which the economics department belongs) does offer "broad guidance on what might normally be expected in courses of different sizes and at different levels," it does *not* require that course grades follow a specific distribution. (For more detail on the grading policy at UofT, see Section 10.3 of the Academic Handbook for Instructors, available at https://teaching.artsci.utoronto.ca/teachinginas/academichandbook/.) Indeed, course grade outcomes do vary from year-to-year. For example, between 2014 and 2018, the faction of students earning As in first-year economics at UTSG varied between 22 and 28 percent, and the fraction of students earning As at UTM varied between 16 and 23 percent. The fraction earning Fs ranged between 7 and 10 percent at UTSG and 11 and 20 percent at UTM.

[33] We do not include grades as an outcome at WGU because WGU does not give traditional grades in courses. Instead, all courses at WGU are graded as pass/fail.

In this section, we present the estimated effects of the planning treatment on student self-reported study times (at UofT), online activity (at WGU), and academic outcomes (at both UofT and WGU), as well as an exploration of heterogeneous treatment effects across various student subgroups.

4.1. Treatment Effects on Student Self-Reported Study Time

We begin by discussing treatment effects on student self-reported study time from the follow-up survey at UofT and activity on the online portal at WGU.

The average student in the control group at UofT spent 15.6 hours studying outside of class during a regular week in the fall semester and 24.8 hours studying when exams were approaching. Table 7 reports estimated treatment effects on both outcomes in the full sample of UofT students and separately by campus. The estimated average treatment effects are presented, with and without control variables, respectively, in columns (3) and (4). Treatment effects on study time during a regular week in the pooled sample range between 1.65 and 1.69 hours and are statistically significant at the 1 percent level. Students who were assigned to the planning treatment therefore self-report studying nearly two more hours during a regular study week than non-treated students and treatment effects are nearly identical across UTSG and UTM, as in indicated in the bottom two panels of Table 7. The estimates in Table 7 also reveal that the planning treatment did not affect student study time during exam or midterm periods, on average, as the effects are small and statistically insignificant in all specifications and across both campuses.

In Figure 6, we further investigate the underlying patterns in the treatment effects throughout the distribution of students by plotting separate densities by treatment and control group for student study time during an average week and for study time during a week with midterms or exams approaching. The average treatment effect on study time during an average

week (reported above) appears to stem from the planning intervention causing fewer students to self-report studying less than 15 hours per week and more students to report studying between 15 and 45 hours per week. The patterns for the densities of study time during an exam period are less clear, as the planning module resulted in more students reporting studying between 17 and 37 hours but fewer students studying above 50 hours. Because of these competing forces, the estimated *average* treatment effect is not statistically differentiable from zero.

In addition to study hours at UofT, we test whether the treatment at WGU affected study frequency as measured by logins and click data. The main outcomes of interest are the number of days per week a student logs into WGU's online portal and the log number of mouse clicks, log number of mouse moves, and log number of page scrolls. Although these data have limitations because students are primarily studying outside of the WGU website, they do contain precise information on frequency and intensity of student interaction with the online portal. Table 8 shows that for all four outcomes the effects of intervention are small and statistically insignificant. Figure 7 underscores this point, showing that the average number of days students log into the WGU website during each week of the semester do not significantly differ across the treatment and control groups.

In sum, we find clear evidence that assignment to the planning-focused warm-up exercise at UofT caused an increase in self-reported study time during an average week and suggestive evidence that it also caused an increase in study time during midterm and exam periods. However, we do not find evidence that treated students at WGU significantly changed their study time in response to the intervention. There are at least three reasons for the contrasting results between UofT and WGU. First, it is possible that the intervention was effective in the UofT sample but not the WGU sample. Second, WGU students may have increased study time but we are not able to

detect it given the limitations of our study time data at WGU. Third, treated students at UofT may have been primed by the treatment materials to inflate their self-reported weekly study time relative to students in the control group. In Section 5, we present supplemental evidence to suggest that treated students being primed is an unlikely explanation for our results, showing that we obtained nearly identical estimates after running a similar experiment the subsequent year at the same UofT campuses. We also use new data from the follow-up experiment to present additional evidence against the priming interpretation of our results.

4.2. Treatment Effects on Achievement Outcomes

Table 9 reports treatment effects for several academic outcomes estimated separately at UTSG, UTM, and WGU. Outcomes at UofT are measured throughout the entire 2017-18 academic year, while outcomes at WGU are recorded for all students who enrolled between January 2 and March 1 of 2017. We define the 'retention' outcome as a binary variable capturing whether a student was enrolled in the winter semester of the 2017-18 academic year at UofT and whether a student was enrolled in the semester following the experimental period at WGU.

The planning treatment appears to have no effect on students' academic outcomes. The results in Table 9 indicate that treated students do not attempt or earn more credits than students in the control group and they are not more likely to persist into second semester. These results are robust across all three experimental sites and to estimating treatment effects with and without other student-level control variables.[34] At WGU, there is suggestive evidence that treatment may have

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[34] At UTSG and UTM, control variables include student age, self-reported study hours per week during high school, expected hours per week studying this semester, expected paid-work hours per week, tendency to think about future goals, tendency to study at the last minute, difficulty transitioning to university, commuting time (in minutes) to campus, and indicator variables for first-year status, international student status, first-generation status, gender, English mother-tongue status, a self-reported desire to earn more than an undergraduate degree, and a self-reported expectation to earn an A- average grade or greater. At WGU, control variables include age, sex, race, first generation status, employment status, and income (bins).

actually reduced retention into next semester, with students in the treatment group being 1.5 percentage points less likely to enroll. This is a small effect, however, corresponding to 1.7 percent of the mean retention rate.

In Table 10, we investigate treatment effects on course grades and GPA at the UofT campuses and the number of days until a student earns his or her first credit at WGU. At UofT, we show treatment effect estimates on course grades from stacked regressions where the unit of observation is a student-course and standard errors are clustered at the student level. We also present estimated treatment effects on courses taken during the fall semester, courses taken during the winter semester, and all courses taken during the full academic year.[35] When the outcome is student GPA from the full academic year, we run the regression at the student-level and report robust standard errors.

The planning intervention did not significantly affect student grade outcomes at either campus of UofT. Furthermore, we are able to rule out grade improvements greater than 0.045 standard deviations at UTSG and 0.032 standard deviations at UTM. This is a fairly precise null effect. For example , Oreopoulos and Petronijevic (2018) find that a personal coaching service in the same UofT context improved grades by 0.30 standard deviations, or between 6.6 and 9.4 times as large as the effects we are able to rule out. This result is robust to considering courses from each semester separately and to including additional control variables. Similarly, at WGU, we find that the planning intervention did not have any impact on the number of days students needed to complete their first credit. We provide a more detailed discussion of these estimated null effects

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[35] Courses from the entire academic year include fall semester courses, winter semester courses, and courses that span both semesters.

in Section 5 below, where we interpret and reconcile these results with the effects of treatment on study time.

4.3. Treatment Effects Across Student Subgroups

We now present estimated treatment effects on academic outcomes across a variety of student subgroups.[36] Specifically, at both the UofT campuses and WGU, we investigate whether treatment effects are differential by student gender, age, employment status, and first-generation status. At the UofT campuses, we also explore potentially different treatment effects across international and domestic students and first-year and non-first-year students; while at WGU, we also differentiate across students by race and by household income.

In Tables 11 and 12, we report the effects of the planning intervention on all course grades across student subgroups at UTSG and UTM, respectively. The planning module does not appear to have caused an improvement in student grades among any subgroup of students at UTSG, as no treatment effect is economically or statistically significant. At UTM, treatment effects are negative and marginally statistically significant (at the 10 percent level) for male students and those who expect to work than 8 hours per week at the start of the academic year. However, given the many hypotheses being tested in the subgroup analyses across UTSG and UTM (24 hypothesis) and the lack of an overall treatment effect in the main sample, we interpret these negative effects cautiously, as they are likely due to chance.

Table 13 explores heterogeneous treatment effects on earned credits across student subgroups at WGU. As in the aggregate analysis, the planning module appears to have no effect

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[36]In our analysis of subgroups (and treatment effects in the full sample above), we closely follow our AEA pre-registered analysis plans (registration ID AEARCTR-0000972 at WGU and AEARCTR-0000810 at UofT).

on credit accumulation for any group of students.[37] In particular, we note that there are no differences in treatment effects across students who are employed full-time, part-time, or unemployed, suggesting that the absence of a treatment effect in the full sample is not driven by students who work full-time not having the time available to increase their study effort. Treatment effects are also similar across students from households with different incomes.

Comparing the estimated treatment effects across all three experimental sites, treatment effects are similar across older (20 years of age or older at UofT and 30 years of age or older at WGU) and younger students, suggesting that student maturity (as proxied by age) is not an important factor in explaining our null treatment effects. It is also the case that treatment effects do not differ by first-generation status (at both UofT and WGU), international student status (at UofT), or first-year status (at UofT), indicating that familiarity with institutional features is also unlikely to be an important moderating factor for treatment effectiveness.

5. Discussion

In this section, we discuss our seemingly contrasting results that treatment increased study time at UofT while having no effect on academic outcomes. We also discuss the implications of our results on the broader literature on student decision-making and interventions in higher education.

5.1. Is the Effect on Study Time Real?

Given the positive effects on study time at UofT and the null effects on grades, one may worry that the study time effect is biased upward by the Hawthorne effect or by treated students being

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[37] Treatment effects across subgroups on credit accumulation and persistence are similarly small and insignificant at both WGU and the campuses of UofT. The results are available upon request.

primed to inflate their self-reported study time relative to students in the control group. We argue that these estimates are unlikely to be upwardly biased for three reasons.

First, supplemental evidence that we obtained from a similar experiment at the UofT campuses during the subsequent academic year (2018-2019) again shows nearly identical first stage effects on study time with subsequent null effects on academic outcomes. In the second experiment, treated students completed a slightly modified version of the planning intervention and were again invited to participate in follow-up text message coaching through the fall semester.[38] Students were also given a follow-up survey at the end of the fall semester in which we asked them how many hours per week they spent studying during typical week and how many hours they spent studying during a week with midterms and exams approaching.[39] This follow-up survey did have grade incentives attached in the second experiment, which resulted in a much higher completion rate of 70 percent.[40] The supplementary evidence we present here thus suffers less from the potential concern that only the most motivated students completed the follow-up survey.

Estimated treatment effects on study time from the second experiment are reported in Table E.1 of Appendix E. In the pooled sample of students from both UofT campuses, treated students report studying approximately 2.2 hours more than control students during a typical week in the fall semester. The effect sizes are similar across the two campuses, with students at UTSG studying about 2.6 hours more per week (14 percent more than the control group) and students at UTM studying 1.7 hours more per week (10 percent more than the control group). Figure E.1 shows that the average treatment effect on study time again stems from the planning intervention causing

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[38] Students in the control group were assigned to complete the same personality test.
[39] In contrast to the follow-up survey used in the first experiment, the question about midterms or exams asked students how many *additional* hours (relative to regular week studying) they study when midterms or exams are approaching.
[40] The completion rate was not differential between the treatment and control groups.

fewer students to study less than 15 hours per week and more students to study between 15 and 45 hours per week. The results in Table E.1 are also consistent with treatment increasing extra study time during exam weeks at both campuses but these estimates are not statistically different from zero.[41]

Second, to mitigate the potential influence of the Hawthorne effect—study participants acting differently because they are being observed—and measurement error concerns that stem from retrospective self-reporting, we asked students in the second experiment to complete a time-use diary, documenting a complete breakdown of how they spent their time "yesterday" – that is, the day before they completed the follow-up survey. In addition to suffering less from measurement error, reported study time in the time-use diaries is also less likely to be biased by the Hawthorne effect or treated students inflating their answers, as students were not informed that time-use diary questions would be asked and the questions did not ask students about study time directly. Instead, we simply asked students to provide a detailed breakdown of how they allocated their time the day before taking the survey, allowing them to select from 17 options, [42] and then constructed total study time "yesterday" as the sum of time spent studying alone, time spent studying with other students, and time spent with a tutor or instructor (outside of class). We then estimated treatment effects on the amount of time students reported studying in their time-use diary, again recovering positive treatment effects at both campuses. Our estimated treatment effects, reported in Table E.2, imply that treated students studied about 0.25 hours more per day, on average, than students

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[41] The second experiment and its full set of results are the subject of a different, standalone paper. For brevity, we do not discuss the estimated treatment effects on academic outcomes from the second experiment in the current paper. In summary, we again do not find economically or statistically significant effects on academic outcomes, both in the full sample and many student subgroups.

[42] The options were: sleeping, attending class, studying alone, studying with others, working for pay, meeting with a tutor or instructor, volunteering, commuting, seeing friends, spending time on a computer, spending time on a phone, watching TV, doing extracurricular activities alone, doing extracurricular activities others, eating alone, eating with others, and other activities not listed above.

assigned to the control group, which amounts to approximately a 6 percent increase in study time relative to the control group mean. The estimated effects on study time are similar across UTSG and UTM and, at approximately 15 minutes per day, align very closely with our estimates for treatment effects on self-reported weekly study time.[43]

Third, although we did not find positive treatment effects on our measures of online activity at WGU, we note that these measures are imperfect proxies for study time. In particular, we only observe activity (log ins, mouse clicks, mouse moves, and page scrolls) in the online portal that links students to external courses.[44] Course content at WGU is hosted by third-party providers, which prevents us from observing actual study time and study intensity.   Even if we did observe online coursework, it is possible that students complete much of their studying offline and simply access their online portals to download course materials. The estimated null effects on our measures of study activity at WGU therefore do not necessarily contradict the positive effects we find at UofT.

5.2. Why is there No Effect on Grades?

Given the positive and robust effect on study time at UofT, it is somewhat puzzling that we find no effect on grades. As noted earlier, however, the association between study time and grades (even after adjusting for measurement error in study time) is relatively weak. We found that an additional 10 hours of studying per week is associated with an increase in mean grades between 2.2 and 4.6 percentage points. We corroborate this finding again using the data gathered from our second experiment at UofT, where we can also instrument for weekly study time using total daily

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[43] As further support for the intervention affecting study time, we note the subsequent experiment was also conducted at the third campus of UofT, the University of Toronto at Scarborough, and another large university in the great Toronto area, York University. Treatment effect estimates at both sites are similar to those reported here and are available upon request.

[44] The online portal also includes a calendar, mentoring resources, testing resources, and financial resources.

study time from the time-use diaries on the follow-up survey. The descriptive associations between study time and grades for the second experimental cohort are reported in Table E.3 in Appendix E and imply (using the IV estimates that are adjusted for measurement error) that an additional 10 hours of weekly study time is associated with an increase in mean grades between 2.25 and 4.93 percentage points, a range nearly identical the one found in our first experimental cohort.

Recall that our estimated treatment effect on weekly study time at UofT is approximately 1.7 hours per week. Evaluating this increase in study time at the estimated upper bound for the association between weekly study time and grades, we would expect to find an average effect on grades of 0.84 percentage points. This is a very small effect and one that we do not have the power to detect.[45] Although our estimate of the return to studying is adjusted for measurement error, it does not reflect a causal link between study time and grades. We attempt to account for this by performing a back-of-the-envelope calculation that uses the estimate of the causal return to study time from Stinebrickner and Stinebrickner (2008), who use time-diary data from Berea College together with an instrumental variables strategy to find that a one-standard deviation increase in studying *per day* increases student GPA by 90 percent of standard deviation.[46] The standard deviation of daily study time in their data is 1.62 hours per day (or 11.34 hours per week) and the standard deviation of GPA is 0.686 points. Importing their estimate of the casual return to studying into our setting, we would expect to find that increasing studying time by 1.7 hours per week (our treatment effect) leads to an increase in GPA of 0.09 points – an effect that would be marginally

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[45] In Table 10, the standard errors on our estimated treatment effects on fall semester grades are 0.584 and 0.735 percentage points and UTSG and UTM, respectively. The point estimates and standard errors together imply 95-percent confidence intervals of [-1.14, 1.15] and [-1.77, 1.10].
[46] Stinebrickner and Stinebrickner (2008) instrument for study time with a variable indicating whether a student's roommate brought a video or computer game to campus.

significant at the 5 percent level but still insignificant at the 1 percent level, given our statistical power.[47]

Another explanation for why the positive effects on studying do not translate into higher grades could be the influence of a John Henry effect—individuals in the control group actively working harder to overcome a perceived disadvantage relative to the treatment group—perhaps via the control group engaging in more productive studying or increasing academic effort outside of studying. While we are unable to observe whether those in the control group are aware of the planning tools provided to the treatment group and whether they changed how they studied in response, we did not record any instances of students in the control group identifying, complaining about, or requesting a change to their treatment status. Furthermore, we find that in the 2018-2019 experiment at UofT, students in treatment group are 4 percentage points less likely to report missing class often (4-7 times during the semester), which is inconsistent with students in the control group working harder to overcome a perceived disadvantage. As a result, we do not believe that a John Henry effect can explain the lack of an effect of our intervention on student grades.[48]

Taken together, our results imply that the planning intervention increased study time by approximately 1.7 hours per week at the UofT campuses but that the association between weekly study time and academic outcomes is not large enough for the treatment effect on study time to translate into an economically and statistically significant effect on course grades and GPA.

5.3. Why Was the Intervention Unsuccessful and What Can We Learn from It?

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[47] Pooling observations from both the UTSG and UTM campuses and including control variables along with campus fixed effects (all in order to *increase* statistical power) results in an estimated treatment effect of 0.002 points on fall semester GPA, with a corresponding 95-percent confidence interval of [-0.068, 0.073] and a 99-percent confidence interval [-0.091, 0.095].

[48] We also note that students at WGU typically do not interact with each other because courses are fully online and asynchronous, meaning that students are very unlikely to be aware of or respond to their treatment status.

In this subsection, we argue that our intervention likely lacked the scale and intensity that are required to meaningfully affect student outcomes. We conclude the section by offering a speculative discussion about the implications of our results for future interventions.

5.3.1. Students Did Engage with the Intervention

UofT students engaged enthusiastically with both the online materials and the text message coaching program. With respect to the materials presented during the online intervention, treated students responded by initially scheduling more study time into their calendars than they reported expecting to study during the (pre-randomization) baseline survey.[49] As shown in the first block of Table E.4 in Appendix E, the average treated student at UTSG scheduled 7 more hours than initially expected at the calendar stage while the average student at UTM scheduled 9.5 hours. Figure E.2 presents the densities of expected and calendar-scheduled study times for treated students at both UofT campuses, showing that treatment caused a rightward shift of the expected study time density, especially for those who planned to study 15 hours or less initially. These increases in planned study time again underscore that binding time constraints are not the reason most students do not study more, as many were able to allocate additional time in their weekly schedules for studying. Further, these results suggest students were reading and processing the materials presented to them during the intervention, as they increased planned study time by a large margin at the calendar building stage.

However, treated students did not follow through with their more ambitious study goals. The second block of estimates in Table E.4 show that the gains in calendar-planned study time over expected study time (at baseline) were completely undone during the semester, as students reported

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[49] Importantly, the balancing tests in Tables 2 and 3 show that expected study time per week is not different across treatment and control groups.

studying (at follow-up) 8.2 hours less than planned (at the calendar-building stage) at UTSG and 9.5 hours less than planned at UTM.[50] Students were unable to follow through with their plans despite receiving weekly text messages that kept their study goals salient and offered help with on-going issues. As indicated in Figure E.3 in Appendix E, approximately 80 percent of students replied to these text messages at least once, with week-to-week response rates varying between 20 and 70 percent. Therefore, not only did students engage with the initial online intervention but many interacted with the text message coaching service as well.[51]

5.3.2. The Intervention was Not Comprehensive Enough to Cause and Sustain the Required Change in Behavior

Given that students seem to have been engaged with the all facets of the intervention, it is likely that the intervention simply did not have the scope and intensity needed to meaningfully affect student outcomes.

As shown above, the associations between study time and outcomes imply that marginal changes in study time are likely not enough to generate a large improvement in academic outcomes; instead, the descriptive relationships suggest large changes in study habits are required to meaningfully impact student grades. Furthermore, high-achieving students differ from low-achieving students along many characteristics other than study time. In Table E.5 in Appendix E, we restrict the sample to students from the control group across both UofT campuses and regress

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[50] The final block in Table E.4 shows the estimated treatment effects on the difference between self-reported study time from the follow-up survey and expected study time at the baseline survey. Students in the control group at UTSG and UTM report studying 3.3 and 2.4 hours less than expected per week, respectively. The treatment effect at both campuses implies that the mean difference among treated students is approximately 2 hours larger, but it is important to note that treated students also studied less than expected.

[51] Supplemental evidence from our second experiment at the UofT campuses indicates that students enjoy participating in these types of coaching programs: 70 percent of participants agreed that the program was helpful for them and 87 percent thought the program should be offered again the following year to a new cohort of students.

several different variables (gathered at baseline) on indicators for students having a fall semester course grade average that is an A or above, a B, a C, or a D and below (the omitted group). Students who earned an A average studied more than all other students and 7 hours more per week than students who earned a D average or less. This difference amounts to approximately 0.54 standard deviations of weekly study time.

But the remaining associations reported in Table E.5 indicate that there are much more stark differences between the best- and worst-performing students along other dimensions. For example, A students have incoming high school grades that are nearly a full standard deviation (0.95 SD) higher than students who earn a D or below, implying that much of the achievement gap is related to pre-existing differences in academic preparedness. In addition, top-performing students hold themselves to a higher standard, expecting to study 3.3 hours more than the worst students and being 18 percentage points (40 percent) more likely to expect to earn an A average in the upcoming semester. Relative to students who earn a D or less, students who earn an A average are also much more likely to believe that they (i) tend to finish what they start (16 percent), (ii) manage their time well (42 percent), (iii) do not study at the last minute for exams (23 percent), and (iv) think about the future (9.6 percent). They also start the online exercise approximately two days earlier at the beginning of the fall semester, which is consistent with them having a lower tendency to procrastinate (Beattie, Laliberte, and Oreopoulos 2018).

These descriptive associations, along with the evidence that treated students drastically failed to reach their calendar study goals, suggest that a more intense intervention is likely required to help students (i) compensate for lower incoming ability, (ii) set and maintain much more ambitious study goals, and (iii) meaningfully change their broader approach to post-secondary studies. Many successful interventions in post-secondary settings offer such exhaustive programs, consisting of

a combination of tutoring, comprehensive and personalized advising, future planning, and some form of financial aid (Scrivener and Weiss 2013; Bettinger and Baker 2014; Andrews, Imberman, and Lovenheim 2016; Evans, Kearny, Perry, and Sullivan 2017). These efforts target a student's entire routine and approach to school, with personal support and frequent encouragement. Less comprehensive, low-touch interventions have proven effective at affecting outcomes that require students to take a series of well-defined steps (Castleman and Page 2015; Castleman and Page 2016), but such programs have largely been unable to affect outcomes such as grades or credit accumulation, which require sustained changes in behavior (Castleman and Meyer 2016; Oreopoulos and Petronijevic 2018).

6. Conclusion

In this study, we examine whether an intervention focusing on study time can improve student outcomes in three distinct academic environments: a selective four-year college, a less selective four-year college, and an online university. Our analysis is motivated by patterns of very low study times observed among students in our populations and documented by other scholars (e.g. Babcock and Marks, 2011). Despite recommendations to treat studying like a full-time job, students at the UofT campuses only report studying 16.8 and 14 hours per week, on average, at UTSG and UTM, respectively. Further, the median student at UTSG studies only 12 hours per week while the median student at UTM studies only 10 hours per week. At WGU students only log on to the course website an average of 2.1 days per week. Although students in each environment appear to have the ability to increase their studying, we find no impacts of our planning treatments on academic outcomes at any of the three academic environments we study and across many demographic subgroups.

We find null effects on academic outcomes despite treated students being highly engaged with the intervention at the UofT campuses – with respect to both the online intervention and text message coaching – and responding to treatment by increasing study time by approximately 2 hours per week. The effect on study time was not large enough, however, to generate a significant change in academic performance, as our estimates of the relationship between study time and grades indicate that we would expect to see at most a 0.84 percentage point (6 percent of a standard deviation) improvement in course grades. Given the large change in study behavior that is required to generate meaningful change in student outcomes and the many other characteristics along which high- and low-performing students differ, it is likely that a more intense and comprehensive intervention that transforms students' approach and attitudes towards education is required to significantly improve academic achievement.

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Tables

Table 1: Randomization Design at UofT

	Full Sample		UTSG		UTM	
	Control	Treatment	Control	Treatment	Control	Treatment
Number of Students	1,849	1,732	1,106	938	743	794
(i) Fraction of total	39.97	37.44	35.82	30.38	48.34	51.66
(ii) Intended fraction	-	-	33	33	50.00	50.00
p-value of (i) = (ii)	-	-	0.001	0.002	0.193	0.193
Completed Exercise	1,802	1,685	1,081	916	721	769

Notes: The fractions in the whole sample and at St. George (UTSG) do not sum to one because the UTSG campus ran another intervention in addition to the time management intervention. Students who received the other intervention are included only in this table to construct the fraction of students in each group. We drop these observations throughout the remainder of the analysis.

Table 2: Balancing Tests at UTSG

	Treatment Status	
	Control	Treatment
Student Characteristics	Sample Mean [Standard Deviation]	Difference [Standard Error]
Male	0.477	-0.016
	[0.500]	[0.023]
Age	18.639	0.017
	[2.070]	[0.092]
High School Admission Average	90.598	-0.263
	[4.078]	[0.232]
English Mother Tongue	0.399	-0.002
	[0.490]	[0.023]
Intends to Earn more than BA	0.739	-0.021
	[0.440]	[0.020]
First Generation Student	0.226	0.013
	[0.418]	[0.019]
Expects to Earn at Least an A- Grade Average	0.481	0.016
	[0.500]	[0.022]
Expected Work Hours in Current Year	6.433	0.077
	[9.172]	[0.414]
Think about the future (1 to 7)	5.614	0.029
	[1.223]	[0.053]
Transition has been so far challenging (1 to 7)	4.571	-0.027
	[1.616]	[0.072]
Tend to cram for exams (1 to 7)	4.099	-0.011
	[1.558]	[0.068]
Expected Study Hours Per Week in University	18.588	-0.500
	[12.177]	[0.537]
Study Hours Per Week in High School	13.665	-0.414
	[11.812]	[0.505]
Time Spent Commuting to Campus (mins)	23.888	0.723
	[27.429]	[1.246]
International Student	0.520	-0.013
	[0.500]	[0.022]
First-Year Student	0.744	-0.010
	[0.437]	[0.020]
Number of Students	2,044	

Notes: Summary statistics and differences are calculated using the full sample of students at UTSG. Robust standard errors are reported in brackets.

Table 3: Balancing Tests at UTM

	Treatment Status	
	Control	Treatment
Student Characteristics	Sample Mean [Standard Deviation]	Difference [Standard Error]
Male	0.519	-0.001
	[0.500]	[0.026]
Age	18.627	0.045
	[1.337]	[0.083]
High School Admission Average	84.976	0.245
	[4.421]	[0.256]
English Mother Tongue	0.401	-0.006
	[0.490]	[0.025]
Intends to Earn more than BA	0.616	0.002
	[0.487]	[0.025]
First Generation Student	0.342	0.006
	[0.475]	[0.024]
Expects to Earn at Least an A- Grade Average	0.404	0.006
	[0.491]	[0.025]
Expected Work Hours in Current Year	8.170	0.436
	[9.639]	[0.495]
Think about the future (1 to 7)	5.546	0.127**
	[1.220]	[0.061]
Transition has been so far challenging (1 to 7)	4.747	-0.028
	[1.583]	[0.081]
Tend to cram for exams (1 to 7)	4.079	0.038
	[1.453]	[0.075]
Expected Study Hours Per Week in University	15.622	-0.530
	[12.229]	[0.611]
Study Hours Per Week in High School	11.794	-0.513
	[10.637]	[0.536]
Time Spent Commuting to Campus (mins)	30.908	1.736
	[30.576]	[1.604]
International Student	0.491	-0.032
	[0.500]	[0.025]
First-Year Student	0.759	0.002
	[0.428]	[0.022]
Number of Students	1,537	

Notes: Summary statistics and differences are calculated using the full sample of students at UTM. Robust standard errors are reported in brackets. ** indicates significance at the 5 percent level

Table 4: Balancing Tests at WGU

	Treatment Status	
	Control	Treatment
Student Characteristics	Sample Mean [Standard Deviation]	Difference [Standard Error]
Male	0.347	0.001
	[0.476]	[0.012]
Age	34.771	0.496**
	[9.120]	[0.238]
Hispanic	0.107	0.001
	[0.309]	[0.008]
White	0.790*	-0.002
	[0.408]	[0.011]
Black	0.108	0.005
	[0.311]	[0.008]
Asian	0.047	-0.006
	[0.212]	[0.005]
Employment status=full time	0.752	0.023**
	[0.432]	[0.011]
Employment status=part time	0.144	-0.014
	[0.351]	[0.009]
Employment status=unemployed	0.104	-0.008
	[0.305]	[0.008]
Income=less than 16, 000	0.070	-0.004
	[0.255]	[0.007]
Income=16, 000 to 24, 999	0.084	0.002
	[0.278]	[0.007]
Income=25, 000 to 34, 999	0.114	-0.010
	[0.318]	[0.008]
Income=35, 000 to 44, 999	0.132	-0.010
	[0.338]	[0.009]
Income=45, 000 to 64, 999	0.196	0.025**
	[0.397]	[0.011]
Income=65, 000 or more	0.404	-0.004
	[0.491]	[0.013]
First generation student	0.423	0.022*
	[0.494]	[0.013]
Number of students	6,065	

Notes: Summary statistics and differences are calculated using the full sample of students at WGU. We observe 3,070 students from the control group and 2,995 from the treatment group. Robust standard errors are reported in brackets. ** indicates significance at the 5 percent level, and * at the 10 percent level.

Table 5: Summary Statistics for Study Habits from Follow-Up Survey at UofT

	Full Sample		UTSG		UTM	
	Control	Treatment	Control	Treatment	Control	Treatment
Regular Week	15.595	17.083	16.756	18.525	13.978	15.483
	[13.135]	[12.262]	[13.885]	[12.959]	[11.842]	[11.241]
Midterms/Exams Week	24.779	24.258	28.142	28.105	20.108	19.966
	[17.922]	[15.253]	[18.667]	[15.766]	[15.072]	[13.434]
Observations	871	848	507	446	364	402

Notes: Summary statistics are calculated using all students at both campuses of UofT who completed the follow-up survey. Standard deviations appear in brackets.

Table 6: Associations Between Weekly Study Time and Student Grade Outcomes

	(1)	(2)	(3)	(4)
Panel A: Mean Grade and GPA Across All Fall Courses				
Dependent Variable:	Mean Fall Grade		Mean Fall GPA	
	OLS	IV Using Baseline Survey	OLS	IV Using Baseline Survey
Study Time/Week	0.118***	0.219***	0.011***	0.017***
	[0.025]	[0.073]	[0.002]	[0.006]
Mean of Dep Var.		68.46		2.42
[Standard Dev.]		[13.03]		[1.05]
Observations	792	792	792	792
Panel B: Mean Grade Across Fall Math and Economics Courses				
Dependent Variable:	Mean Fall Math Grade		Mean Fall Economics Grade	
	OLS	IV Using Baseline Survey	OLS	IV Using Baseline Survey
Study Time/Week	0.174***	0.456***	0.135***	0.351***
	[0.055]	[0.134]	[0.043]	[0.112]
Mean of Dep Var.		67.84		67.44
[Standard Dev.]		[16.11]		[15.15]
Observations	284	284	441	441

Notes: The dependent variable in each regression is indicated in the column headings. All regressions are run at the student level and pool all control group observations from the UofT campuses while including campus fixed effects. In columns (2) and (4), we instrument for weekly study time using expected weekly study time at the baseline survey, the expected number of hours students expect to work for pay each week, commute time to campus, self-reported hours spent studying per week in high school, and self-reported tendency to study at the last minute. Robust standard errors are reported in brackets. *** indicates significance at the 1 percent level.

Table 7: Treatment Effects on Self-Reported Study Times at UofT

(1) Sample and Dependent Variable	(2) Control Mean [Standard Deviation]	(3) Treatment Difference	(4) Treatment Difference
Pooled UofT Sample			
Regular Week Study	15.595	1.651***	1.691***
	[13.135]	[0.609]	[0.582]
		1,719	1,628
Exam Week Study	24.779	-0.084	0.196
	[17.922]	[0.779]	[0.748]
		1,714	1,623
UTSG			
Regular Week Study	16.756	1.769**	1.618*
	[13.885]	[0.870]	[0.844]
		953	873
Exam Week Study	28.142	-0.037	0.153
	[18.668]	[1.117]	[1.093]
		951	871
UTM			
Regular Week Study	13.978	1.505*	1.633**
	[11.842]	[0.836]	[0.796]
		766	755
Exam Week Study	20.108	-0.142	0.282
	[15.702]	[1.063]	[1.001]
		763	752
Controls?		No	Yes

Notes: The dependent variable in each regression and the sample used are indicated in the rows of column (1). The unit of observation is a student. Control variables include student age, self-reported study hours per week during high school, expected hours per week studying this semester, expected paid-work hours per week, tendency to think about future goals, tendency to study at the last minute, difficulty transitioning to university, commuting time (in minutes) to campus, and indicator variables for first-year status, international student status, first-generation status, gender, English mother-tongue status, a self-reported desire to earn more than an undergraduate degree, and a self-reported expectation to earn an A- average grade or greater. Robust standard errors are reported in brackets in columns (3) to (4). Pooled estimates include campus fixed effects. The number of observations used in each regression appears below the standard errors. *** indicates significance at the 1 percent level; ** indicates significance at the 5 percent level; and * indicates significance at the 10 percent level.

Table 8: Treatment Effect on Click Data at WGU

(1) Dependent Variable	(2) Control Mean [Standard Deviation]	(3) Treatment Difference	(4) Treatment Difference
Fraction of Days Logged in	0.417	0.003	0.001
	[0.185]	[0.005]	[0.005]
		6,065	6,065
Log Mouse Clicks	7.148	0.026	0.019
	[0.685]	[0.018]	[0.018]
		6,065	6,065
Log Mouse Moves	8.269	0.031	0.020
	[0.724]	[0.019]	[0.019]
		6,065	6,065
Log Scroll Count	10.491	0.033	0.030
	[0.952]	[0.024]	[0.025]
		6,065	6,065
Controls?		No	Yes

Notes: The dependent variable in each regression is indicated in the rows of column (1). The unit of observation is a student. Control variables include age, sex, race, first generation status, employment status, and six income bins: (1) less than 16,000, (2) 25,000-34,999. (3) 35,000-44,999, (5) 45,000-64,999, and (6) 65,000+. Robust standard errors are reported in brackets in columns (3) to (4). The number of observations used in each regression appears below the standard errors.

Table 9: Treatment Effects on Credit Accumulation and Retention

(1) Dependent Variable and Sample	(2) Control Mean [Standard Deviation]	(3) Treatment Difference	(4) Treatment Difference
Credits Attempted			
UTSG	3.799	0.025	0.026
	[1.243]	[0.058]	[0.056]
		1,860	1,860
UTM	3.611	0.030	0.035
	[1.370]	[0.070]	[0.068]
		1,484	1,484
WGU	16.987	0.225	0.226
	[9.107]	[0.234]	[0.228]
		6,064	6,064
Credits Earned			
UTSG	3.479	0.011	0.010
	[1.425]	[0.065]	[0.064]
		1,860	1,860
UTM	3.193	-0.119	-0.114
	[1.557]	[0.080]	[0.078]
		1,484	1,484
WGU	14.434	0.161	0.144
	[10.553]	[0.273]	[0.267]
		6,064	6,064
Retention			
UTSG	0.997	0.002	0.002
	[0.054]	[0.002]	[0.002]
		1,860	1,860
UTM	0.999	0.001	0.001
	[0.037]	[0.001]	[0.001]
		1,484	1,484
WGU	0.891	-0.014*	-0.016*
	[0.312]	[0.008]	[0.008]
		6,064	6,064
Controls?		No	Yes

Notes: The dependent variable in each regression and the sample used are indicated in the rows of column (1). The unit of observation is a student. Control variables used in the UofT samples are described in the notes of Table 7. Control variables use in the WGU sample are described in the notes of Table 8. Robust standard errors are reported in brackets in columns (3) to (4). The number of observations used in each regression appears below the standard errors. * indicates significance at the 10 percent level.

Table 10: Treatment Effects on Grades at UofT and Days to Completion at WGU

(1)	(2)	(3)	(4)
	Control Mean	Treatment	Treatment
Sample and Dependent Variable	[Standard Deviation]	Difference	Difference
UTSG			
Fall Grades (2017-18)	71.020	0.039	0.002
	[14.954]	[0.622]	[0.584]
		5,413	5,413
Winter Grades (2017-18)	69.680	-0.724	-0.648
	[17.023]	[0.740]	[0.714]
		4,894	4,894
All Grades (2017-18)	70.306	-0.436	-0.463
	[16.043]	[0.584]	[0.551]
		12,241	12,241
GPA (2017-18)	2.507	-0.018	-0.022
	[0.996]	[0.046]	[0.044]
		1,860	1,860
UTM			
Fall Grades (2017-18)	66.447	-0.447	-0.338
	[13.622]	[0.755]	[0.735]
		2,951	2,951
Winter Grades (2017-18)	66.470	-1.380	-1.159
	[16.366]	[0.978]	[0.939]
		3,143	3,143
All Grades (2017-18)	66.010	-1.203	-1.104
	[15.747]	[0.764]	[0.739]
		8,428	8,428
GPA (2017-18)	2.119	-0.025	-0.021
	[0.998]	[0.054]	[0.053]
		1,484	1,484
WGU			
Days to First Completion	33.587	-0.258	-0.238
	[27.299]	[0.731]	[0.750]
		5,762	5,762
Controls?		No	Yes

Notes: The dependent variable in each regression and the sample used are indicated in the rows of column (1). Control variables used in the UofT samples are described in the notes of Table 7. Control variables use in the WGU sample are described in the notes of Table 8. When the outcome is course grades, standard errors are clustered at the student level and the unit of observation is a student-course. For other outcomes, robust standard errors are reported, and the unit of observation is a student. Sample size from the regression appears below the standard error.

Table 11: Treatment Effects on Course Grades by Student Subgroup at UTSG

(1) Subgroup	(2) Observations	(3) Control Mean [Standard Deviation]	(4) Treatment Difference	(5) Treatment Difference
Male	5,799	70.231 [16.398]	-0.313 [0.916]	-0.384 [0.862]
Female	6,442	70.377 [15.704]	-0.547 [0.745]	-0.574 [0.692]
Age>=20	1,812	69.677 [17.671]	-1.668 [1.886]	-1.784 [1.809]
Age<20	10,429	70.425 [15.715]	-0.264 [0.604]	-0.042 [0.564]
International Student	6,427	69.376 [16.105]	-0.080 [0.812]	-0.365 [0.746]
Domestic Student	5,814	71.390 [15.904]	-0.924 [0.833]	-0.824 [0.787]
Expected Weekly Work Hours>=8	3,724	68.051 [16.859]	-0.573 [1.059]	-0.691 [0.982]
Expected Weekly Work Hours<8	8,517	71.367 [15.533]	-0.541 [0.689]	-0.411 [0.659]
First-Generation Student	2,649	67.421 [16.401]	-0.015 [1.293]	-0.489 [1.262]
Not First-Generation Student	9,592	71.056 [15.864]	-0.455 [0.648]	-0.403 [0.614]
First-Year Student	9,444	71.264 [15.326]	-0.564 [0.614]	-0.340 [0.590]
Not First-Year Student	2,797	67.123 [17.864]	-0.109 [1.445]	-0.609 [1.355]
Controls?			No	Yes

Notes: The dependent variable in each regression is course grades. Control variables are described in the notes of Table 7. The subsample of students used for each regression is indicated by the rows of column (1). The unit of observation in each regression is a student-course and standard errors are clustered at the student level.

Table 12: Treatment Effects on Course Grades by Student Subgroup at UTM

(1) Subgroup	(2) Observations	(3) Control Mean [Standard Deviation]	(4) Treatment Difference	(5) Treatment Difference
Male	4,270	65.030 [16.353]	-2.390** [1.153]	-1.902* [1.095]
Female	4,158	67.009 [15.044]	0.040 [0.971]	-0.083 [0.953]
Age>=20	1,398	64.571 [16.806]	-1.171 [2.012]	-1.154 [2.006]
Age<20	7,030	66.300 [15.512]	-1.217 [0.823]	-0.921 [0.783]
International Student	3,744	64.969 [15.941]	-1.101 [1.137]	-1.293 [1.113]
Domestic Student	4,684	66.902 [15.528]	-1.391 [1.029]	-0.678 [0.988]
Expected Weekly Work Hours>=8	3,579	65.378 [16.024]	-1.939 [1.198]	-1.918* [1.158]
Expected Weekly Work Hours<8	4,849	66.474 [15.529]	-0.650 [0.989]	-0.680 [0.947]
First-Generation Student	2,862	64.058 [16.164]	-1.144 [1.316]	-0.806 [1.278]
Not First-Generation Student	5,566	66.996 [15.442]	-1.199 [0.932]	-1.125 [0.905]
First-Year Student	6,303	66.730 [15.147]	-0.522 [0.788]	-0.294 [0.774]
Not First-Year Student	2,125	63.898 [17.223]	-3.291* [1.865]	-2.764 [1.799]
Controls?			No	Yes

Notes: The dependent variable in each regression is course grades. Control variables are described in the notes of Table 7. The subsample of students used for each regression is indicated by the rows of column (1). The unit of observation in each regression is a student-course and standard errors are clustered at the student level. ** indicates significance at the 5 percent level; and * indicates significance at the 10 percent level.

Table 13: Treatment Effects on Earned Credits at WGU by Student Subgroup

(1) Subgroup	(2) Observations	(3) Control Mean [Standard Deviation]	(4) Treatment Difference	(5) Treatment Difference
Male	2110	15.130	0.083	0.128
		[12.130]	[0.525]	[0.515]
Female	3955	14.063	0.228	0.200
		[9.592]	[0.311]	[0.303]
Age >= 30	3820	14.644	0.423	0.330
		[10.535]	[0.351]	[0.341]
Age < 30	2245	14.089	-0.329	-0.199
		[10.578]	[0.433]	[0.423]
Black	670	11.172	-1.250*	-0.788
		[10.627]	[0.760]	[0.691]
White	4781	15.060	0.311	0.259
		[10.715]	[0.312]	[0.307]
Hispanic	651	12.339	0.652	0.469
		[7.499]	[0.657]	[0.677]
Employed full time	4465	13.998	0.202	0.281
		[9.740]	[0.292]	[0.289]
Employed part time	801	15.216	-0.360	-0.348
		[9.740]	[0.292]	[0.289]
Not Employed	580	14.879	-0.037	-0.055
		[10.325]	[0.769]	[0.771]
First generation student	2631	13.679	0.306	0.365
		[9.708]	[0.388]	[0.374]
Household income below 45, 000	1838	13.005	0.322	0.524
		[10.875]	[0.501]	[0.463]
Household income above 45, 000	4227	15.082	0.044	0.001
		[10.341]	[0.325]	0.325]
Controls?			No	Yes

Notes: The dependent variable in each regression is earned credits. Control variables are described in the notes of Table 8. The subsample of students used for each regression is indicated by the rows of column (1). The unit of observation in each regression is a student and robust standard errors appear in brackets. * indicates significance at the 10 percent level.
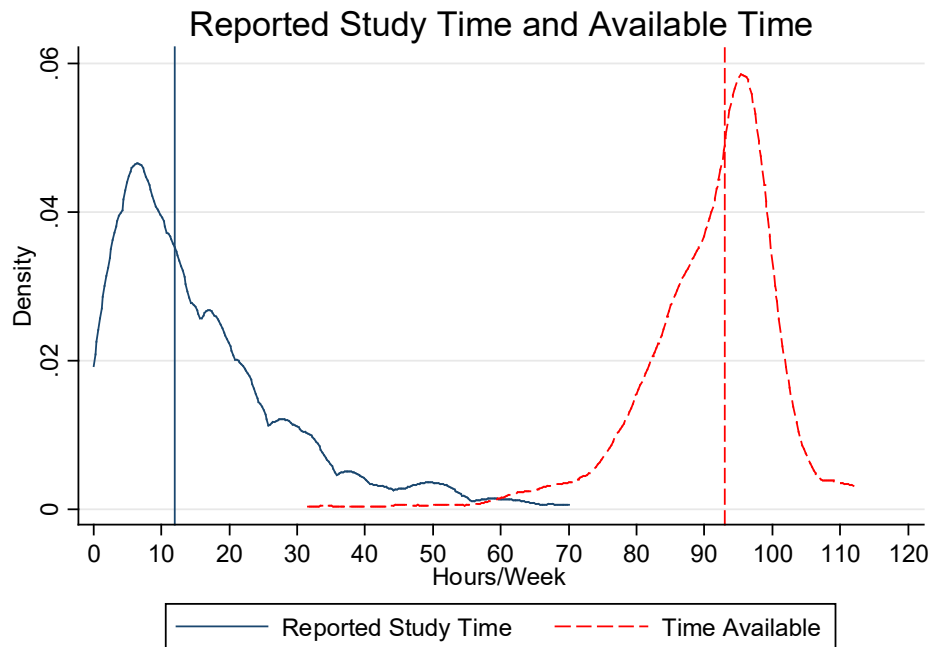
Figures

Figure 1: Student Time Use

Notes: In this figure, time available is constructed as 168 (the number of hours in a week) minus 56 hours per week for sleeping (8 hours * 7 days), students' self-reported expectation for the number of hours they will work for pay per week, students' self-reported commuting time to and from campus each week (in hours), and the time (in hours) spent in class each week (for each class, we assume three hours per week). Reported study time is gathered from student responses to a follow-up survey at the end of first semester and represents the number of hours students report having studied during a regular week in first semester. The vertical lines represent the median of each outcome. The sample used to construct the figure consists of the 871 control group students across both campuses of UofT who answered the follow-up survey.
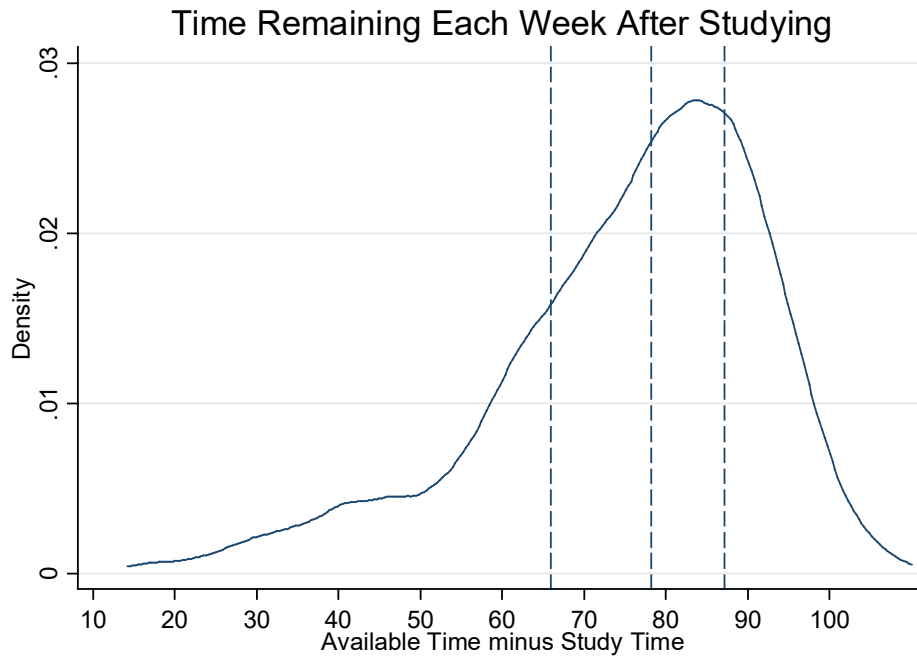
Figure 2: Student Time Remaining After Studying

Notes: This figure presents the density of time remaining after subtracting students' self-reported study time from their available time. The notes of Figure 1 provided details pertaining to the construction of available time. From left to right, the vertical lines represent the 25th, 50th, and 75th, percentiles of time remaining, respectively. The sample used to construct the figure consists of the 871 control group students across both campuses of UofT who answered the follow-up survey.
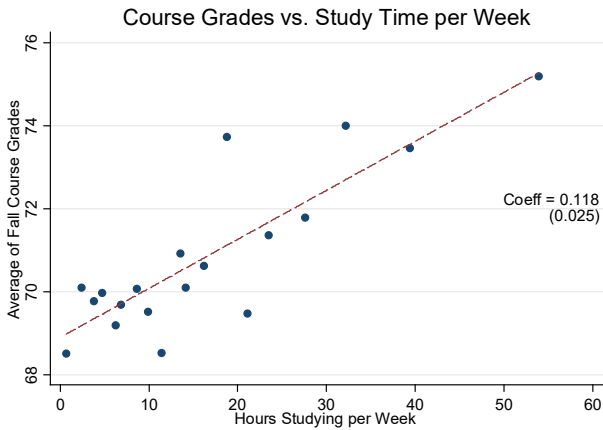
(a): Average of Fall Course Grades
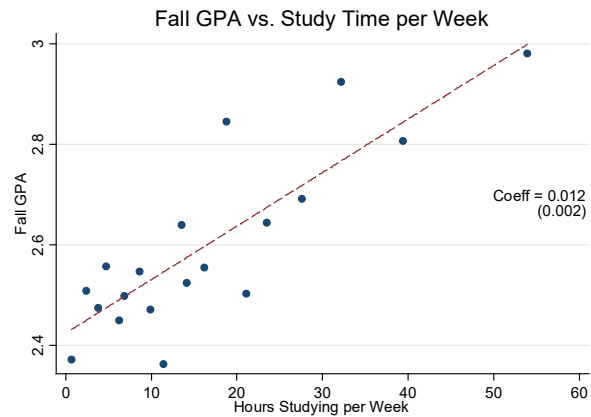
(b): Fall GPA
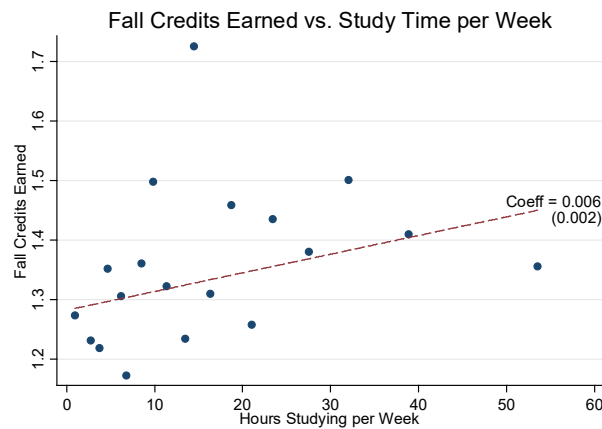
(c): Credits Earned in Fall Semester

Figure 3: Relationships between Fall Semester Study Time and Academic Outcomes at UofT

Notes: This figure presents estimated associations between the number of hours students self-report studying during a regular week in the fall semester and various academic outcomes in that semester. In panels (a), (b), and (c), respectively, the outcomes are average grade across all fall semester courses, grade-point average (GPA) across all fall semester courses, and the number of credits earned during the fall semester. The sample in each panel is restricted to students in the control group across both campuses of UofT. We construct each panel by first grouping students into 20 equally-sized (vingtile) bins of the study time distribution and then calculating the mean study time and outcome within each bin. The blue circles in each panel represent these means, while the red dashed lines represent the associated linear relationships, estimated on the underlying student-level data. Each regression controls for campus fixed effects.
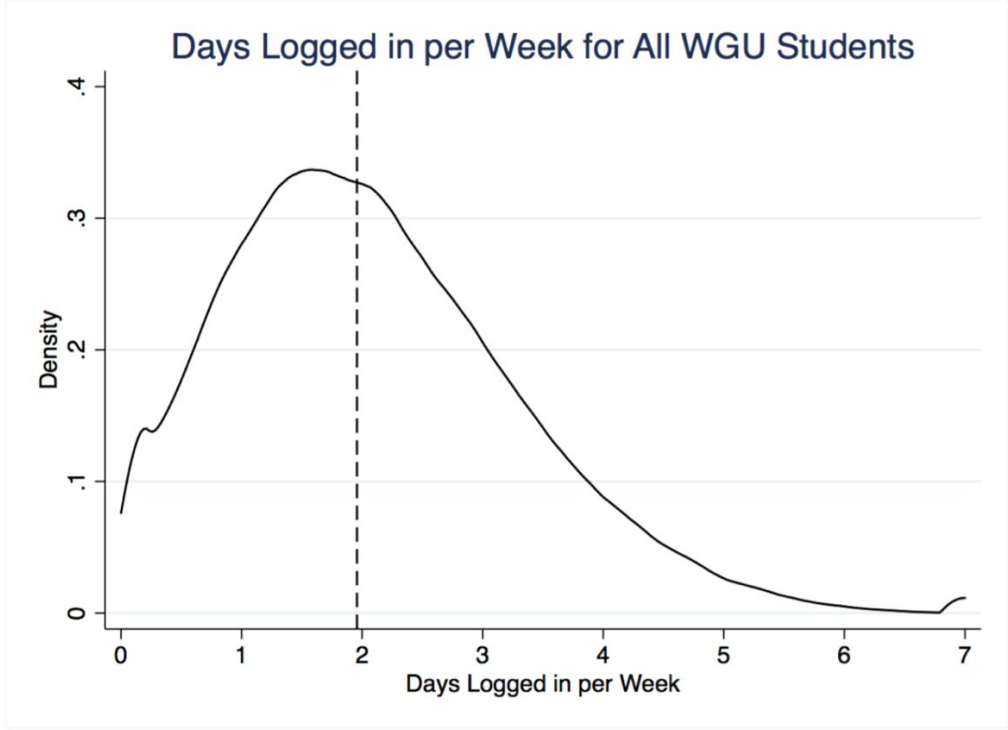
Figure 4: Days Logged in Per Week

Notes: This figure shows the distribution of the average number of days a student logs into WGU's online portal per week. The data used is for all WGU students from January 1, 2015 to July 23, 2018. The vertical line represents the median of the average number of days per week a student logs in.
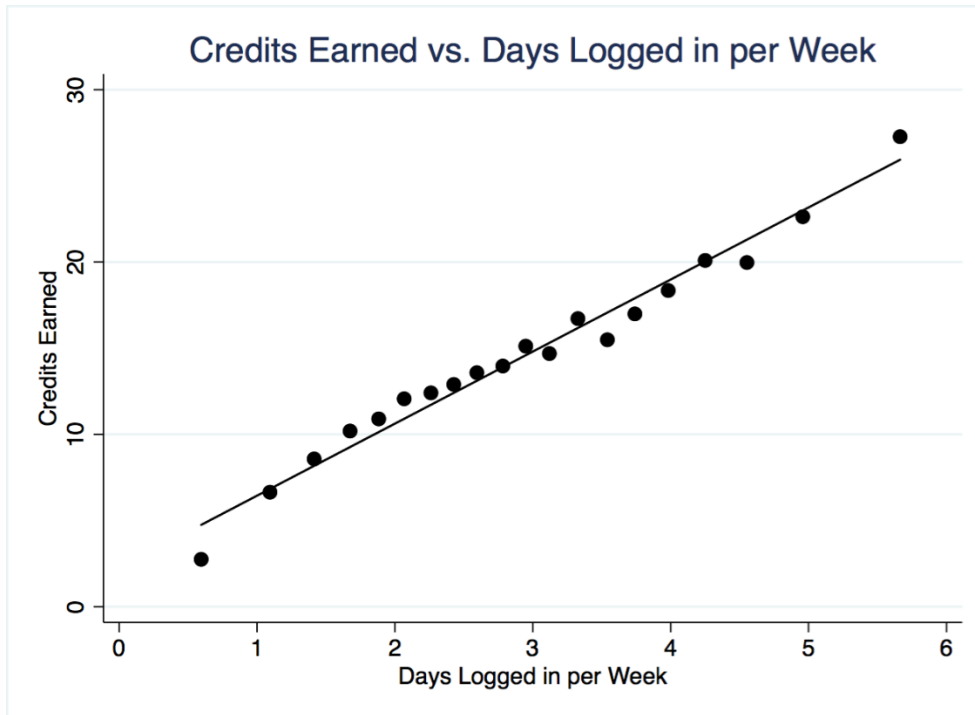
Figure 5: Relationship between Days Logged in and Credits Earned at WGU

Notes: This figure presents estimated association between the days per week students log in to the WGU web portal and credits accumulated during the semester. The sample is restricted to students in the control group at WGU. We construct this figure by first grouping students into 20 equally-sized (vingtile) bins in the distribution of the mean number of days logged in per week and then calculating the mean number of credits earned within each bin. The plotted circles represent these means, while line represents the associated linear relationship, estimated on the underlying student-level data.

Study Time During Regular Week
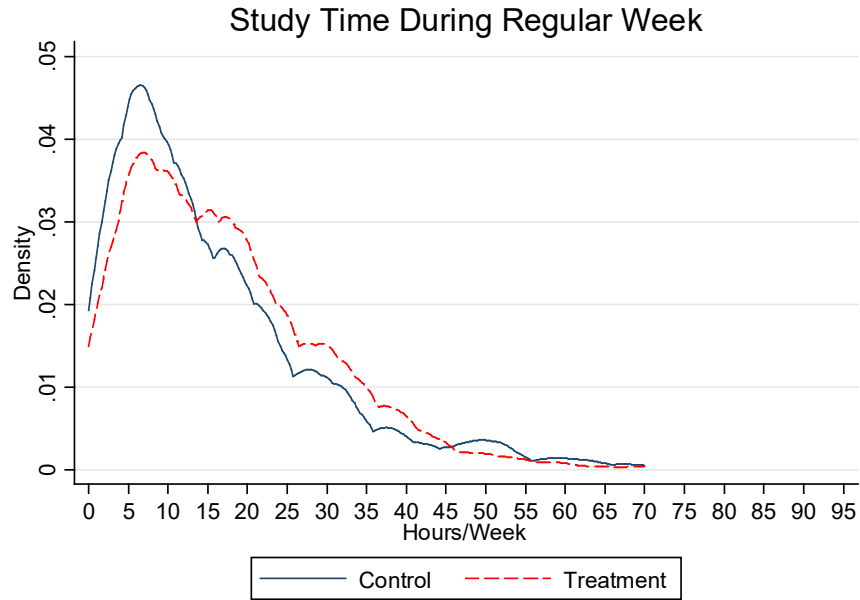
(a): Density of Student Study Time During a Regular Week

Study Time During Exams
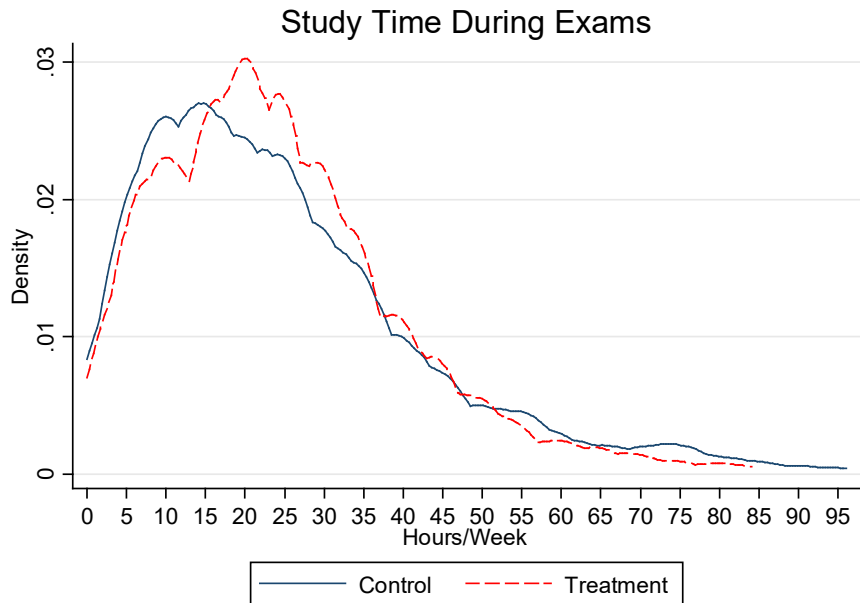
(b): Density of Student Study Time During a Exams

Figure 6: Densities of Study Time

Notes: Panel (a) presents the densities of student study time during an average regular week without midterms or exams approaching. Panel (b) presents the densities of student study time during a week with midterms or exams approaching. The blue solid line in each panel is the density for the control group; the red dashed line in each panel is the density for the treatment group. The samples in each panel consist of students across both campuses of UofT.
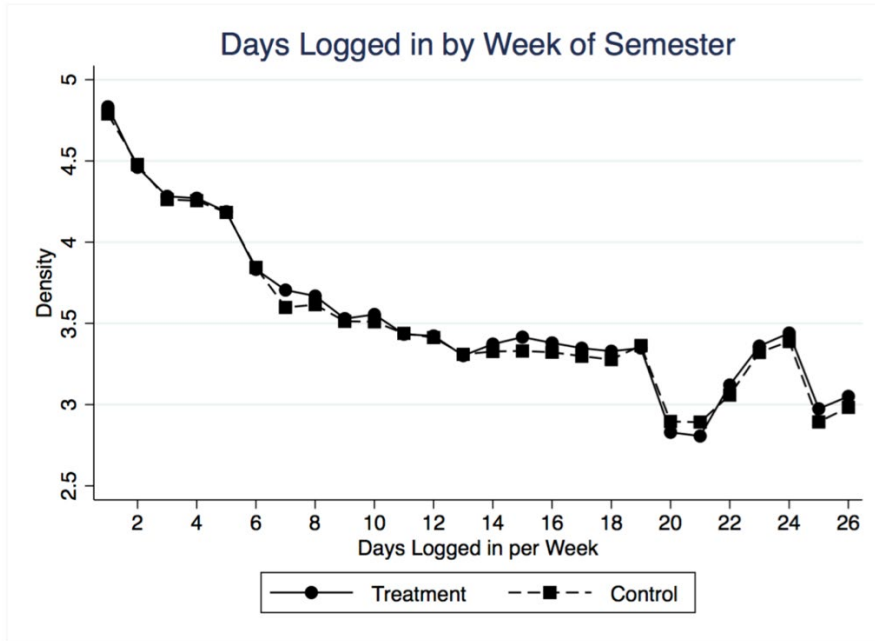
Figure 7: Days Logged in By Week of Semester

Notes: This figure shows the average number of days students log into the WGU website for each week during their first semester. The solid line is for the treatment group and the dashed line is for the control group. The data used is for WGU students in the experimental sample.