Information and credible sanctions in curbing online cheating among undergraduates: a field experiment

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Abstract

The rapid increase in online instruction in higher education has heightened concerns about cheating. We use a randomized control design to test whether informing students that we can detect plagiarism reduces cheating. We further test whether informing students they have been caught cheating reduces subsequent cheating. We find informing students about our capability to detect plagiarism has no effect on cheating. Notifying students that they have been caught cheating and are on a watch list reduces subsequent cheating attempts by roughly 80 percent. We test for peer effects but conclude we cannot credibly identify peer effects distinct from own-cheating propensities. **Keywords:** information, sanctions, cheating **JEL No.** I23, J24

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1 Introduction

Online college courses and degree programs have expanded dramatically over the past ten years. This growth heightened long-standing concerns about cheating and plagiarism given the ease with which material can be acquired and shared electronically. But there is also software that screens assignments for plagiarism, which increases the probability of detection. Whether the net result is an increase in cheating is not well-known (Watson and Sottile, 2010).

In this study we use experimental methods to ascertain the extent of cheating and assess efforts to deter it. The setting is a large public university in which undergraduates have to complete a learning module to develop their facility with Microsoft Excel. The software requires students to download a file, build a specific spreadsheet, and upload the file back into the software.[1] The software grades and annotates their errors. Students can correct their mistakes and resubmit the assignment two more times. Students have to complete between 3 to 4 projects over the course of the semester depending on the course. Unbeknownst to the students, the software embeds an identifying code into the spreadsheet. If students use another student's spreadsheet, but upload it under their name, the software will indicate to the instructor that the spreadsheet has been copied and identify both the lender and user of the plagiarized spreadsheet. Even if a student copies just part of another student's spreadsheet, the software will flag the spreadsheet as not the student's own work.

Since 2015, the syllabus for the module, under the sub-heating "Academic Integrity," has included an explicit statement that students should do their own work along with a reminder of the importance of Excel skills in the job market. Despite the exhortation, copied projects rose from 2.3 percent in the fall of 2016 to 14.9 percent in the fall of 2018 (Figure 1). We have no way of knowing whether students read the statement on academic integrity, which faculty included with their course syllabus. We also don't know whether the rising rate of plagiarism was because students determined they could use other student's work without fear of detection and whether students shared this information with others.

[1] Cengage's Skills Assessment Manager (SAM^{TM}).

As a first step in devising a strategy to deter cheating, we designed an experiment to determine whether direct messages to students regarding our ability to detect cheating would curb it or whether we needed some form of sanction before students appreciated the seriousness of cheating. To address these questions we randomly divided students in each of the four courses into groups A and B ($n = 3,580$). Each course had multiple sections. Students were unaware which group they were in. We first amended the course syllabus statement on academic integrity. We reminded students to submit their own work but we explicitly informed them that the software could detect any work copied from another student. Furthermore, the software could identify both the sender and the user of the plagiarized material. This information was available to both groups A and B via the course syllabus. One week before the first assignment was due, we sent an email to group A reminding students to submit their own work and that the software could detect any work they copied from another spreadsheet. The email further stated that those caught cheating on the first assignment would be put on a watch list for subsequent assignments. Further violations of academic integrity would involve their course instructor for further disciplinary action. Group B received the same email one week before the second assignment. All students flagged for cheating in either of the two assignments were sent an email informing them that they were currently on a watch list for the rest of the semester's assignments.

We find that warning students about the software's ability to detect cheating has no effect on cheating rates. Flagging cheaters, however, and putting them at risk for sanctions lowers cheating by approximately 75 percent. An important question that we can not address effectively was the presence of spillover or peer effects (Sacerdote, 2001; Carrell et al., 2008, 2013). We explore models that use mean cheating rates in a section of a course on own cheating but we conclude that we can not separately identify own effects from peer effects. (Angrist, 2014).

Our study contributes to the literature on cheating among college students in several novel ways. First, we ascertain the extent of cheating with software. Most early reports of college cheating are based on student surveys, and with a few exceptions, are limited to a single institution or course. The extent of self-reported cheating of any kind is as high as 82 percent (Bowers, 1964; McCabe and Trevino, 1997; McCabe et al., 2001b). Specific forms of cheating such as submitting another student's report as one's own are as low as three percent (Karlins et al., 1988). More recent studies of cheating in the age of the internet use proprietary software such as Turnitin.com to evaluate the originality of students' written assignments (Ledwith and Rísquez, 2008; Walker, 2010; Dee and Jacob, 2012). Turnitin provides a similarity score. Researchers present scales of similarity or they create a binary indicator of plagiarism based on a specific threshold of similarity after careful screening for false positives (Dee and Jacob, 2012). Turnitin and similar software, however, cannot readily detect contract cheating in which students pay others to do their work or obtain work from sources not in databases accessible by Turnitin (Rogerson, 2017).

Our study is novel in that we evaluate Excel spreadsheets instead of writing assignments. Any part of the spreadsheet that comes from another source is flagged by the software. Thus, there is no discretion as to the determination of cheating. Moreover, the system is largely, but not completely closed, as there is unlikely to be any relevant material on the internet specific to these projects that students can enter as their own. Students are encouraged to use Google for help with Excel as we consider that part of the learning process. A disadvantage is that the software must identity both the sender and user for us to flag the student for cheating. There are cases in which material in the spreadsheet is from an unidentified source. In this case we assume no cheating, which may be be a false negative.

A second contribution is that we can test whether students who are informed that they used another student's work on their first assignment, are less likely to do so on subsequent assignments. Two studies using Turnitin across multiple assignments find that students whose first assignment is flagged for similarity to material from other sources reduce their plagiarism (Ledwith and Rísquez, 2008; Walker, 2010). However, as noted before, Turnitin generates a similarity score. Thus, a reduction in plagiarism can mean a student whose first assignments matches 80-100 percent of the text from another source, but whose second assignment matches 35 percent of the text from another source can be classified as a reduction in cheating. In our study there is less ambiguity. Students who use all or any other part of another student's spreadsheet in their first assignment are warned of more serious sanctions if cheating is detected on subsequent assignments. The first email or warning is informational and devoid of any explicit sanction. We are testing whether making students more aware that we can detect cheating deters it. Once flagged for cheating, the second email informs them that the detection system is genuine and puts them at risk for sanctions should the behavior continue.

A third advance of our study is the use of experimental methods with large samples. Most studies of student cheating rely on surveys of students (McCabe et al., 2001a; Teixeira and Rocha, 2010; Watson and Sottile, 2010; Power, 2009; Carrell et al., 2008). Others describe characteristics of students that plagiarize using software such as Turnitin (Walker, 2010). Another set of studies compares student performance on exams in proctored or un-proctored settings (Harmon and Lambrinos, 2008; Hollister and Berenson, 2009; Hylton et al., 2016). In one study the authors randomly assign 380 students in an online class to an exam proctored by a webcam (N=186) and the other half to un-proctored exam (N=186). There is no difference in students' scores on the exams between the treatment and control group (Hylton et al., 2016).

In an impressive study of plagiarism, authors analyze the writing assignment of 573 students and 1,256 writing assignments for plagiarism using the software Turnitin (Dee and Jacob, 2012). The setting is a select post-secondary institution. The research question is whether improving students' understanding of plagiarism and how to avoid it can lessen its prevalence. The treatment consists of a mandated online tutorial on plagiarism administered at the beginning of the course. The authors find that 3.3 percent of students' assignments in the control group are plagiarized but only one percent of assignments in the treatment group. Students in the lower end of the SAT distribution are more likely to plagiarize their assignment, but the tutorial causes a larger reduction in cheating among this subset. Based on the post-class survey, the authors conclude that the tutorial is effective because it educates students as to what constitutes plagiarism rather than increasing their perceived risk of being caught. Our study is different from Dee and Jacob (2012) in that we focus on two aspects of deterrence: information regarding the probability that one might be flagged for cheating and an explicit response if caught cheating.

2 Conceptual Motivation

Our simple conceptual framework is a slight modification of Dee and Jacob (2012). We start with the assumption that achieving a good grade in the Excel module will improve students' marketability (M) with direct returns of w. M is a function of how much effort (E) students exert, their ability (A) and whether or not they cheat on an assignment (CH). Cheating improves their marketability through a higher grade and a signal to an employer of a valued skill $\frac{\delta M}{\delta CH} > 0$. Cheating, however, increases the risk of being caught (π) and sanctioned (S), which should deter cheating. Warnings that the software can detect cheating (I) should also deter cheating $\frac{\delta pi}{\delta I} < 0$. Effort on assignments increases the opportunity cost of not putting the time and energy elsewhere c(E,A), but lessens the need to cheat. Students chose a level of CH and E to maximize their objective function

$$U = wM(E, A, CH) - c(E, A) - S\pi(E, I, CH). \tag{1}$$

For any level of effort, students must balance the gains to cheating against the expected costs $(w\frac{\delta M}{\delta ch} - S\frac{\delta \pi}{\delta ch})$.

Our experiment manipulates I and S with the goal of deterring cheating. Unlike Dee and Jacob (2012) we assume that students know that sharing work constitutes cheating. As Dee and Jacob (2012) noted, we contend that students are less knowledgeable as to what constitutes plagiarism in writing assignments than explicitly asking for another student's work.

3 The Experiment

3.1 Software and Setup

The setting is a large public urban university in the spring of 2019.[2] Students from four introductory classes in business, two in Accountancy, one in Finance and one in Management, are included in the

[2]The experiment is registered under AEA registry RCT ID AEARCTR-0003786.

study.[3] Each course has multiple sections with an average of 1,000 students per course and roughly 80 students per section. Exceptions include two large online sections in the two Accountancy courses. All students enrolled in all four courses are included in the experiment.

Students in each course are required to build 3 to 4 Excel spreadsheets over the course of the semester from detailed instructions that are generated from Cengage's Skills Acquisition Manager or SAM™, a proprietary software that builds facility with Excel and other business software. Each student has a password-protected account with the software. For each assignment students download the shell of the spreadsheet they have to build along with the requisite data and step-by-step instructions. They also download a picture of what the finished spreadsheet should look like. The software assigns a name to the spreadsheet shell such as "npp.John.Doe.xlsx".

There are 14 different assignments distributed across the four courses. In no two classes are the assignments the same. Each assignment emphasizes various skills with Excel from formatting, to plotting, to pivot tables and basic macros. Each assignment has a specific due date that varies by course. Students can upload their completed spreadsheets to their account any time before the due date. The software grades the submission and provides detailed annotation for each error. Students can correct the errors and re-submit the assignment. Students can submit the spreadsheet for grading three times. Once their assignment is at least 80 percent correct, they are awarded full credit.

Assignments submitted after the due date are penalized one percentage point for each day past the due date. Nevertheless, students can still receive full credit if their final score is at least 80 percent after deducting points for lateness. Thus, students still have incentives to cheat after the due date.

A group of graduate students, under the supervision of a faculty member administer the Excel module. The module is best described as a carve-out from the course. Faculty who teach sections of the course assign between 5 to 8 percent of their course grade to the completion of the Excel module. Faculty have no other responsibility for the module. The graduate students handle all

[3] A fifth course in computer science, which has two excel assignments and is managed by a different administrator, is also included in the warning experiment. With only two Excel assignments, we can not test the effect of sanctions on cheating in the third assignment, and thus, we exclude this fifth course from the analysis. The results for the effects of warning in this course, insignificant and small, are not qualitatively different from the results in the other 4 courses.

correspondence with students. At the end of the semester, the graduate students send each faculty the students' scores on the assignments. If a student completes none of the Excel assignments, he/she loses at least half a grade for the course. Given grade competition, this provides a strong incentive to submit the assignments. Of the 3,578 students enrolled in the four pre-business classes, 3,045 enroll in the Excel module and 2,566 or 71.7% complete all assignments.

3.2 Inclusion criteria

We received a waiver of consent from IRB. Therefore everyone enrolled in the course before the first treatment occurs is included in the study. There are a few students that complete assignments in SAM™ that we can not match to their information from the university data system from which we randomize. This is true of 1.1% (n=5) of students who use SAM™ and who cheated in some class at some point in the semester and 0.9% (n=35) of students who use SAM™ overall. This could be because they enrolled after the first treatment or it could be because their information in SAM™ does not match their information in the university system. These students are excluded from analysis.

In addition, there are students that choose not to use SAM™. About 15% of students do not complete any assignments in SAM™. If they do not complete any assignments they are excluded from the analysis. The difference in the percent of students in group A and group B that do complete assignments is only 1.6 percentage points.

3.3 Identification of Plagiarism

The software embeds a unique code in the worksheet shell as soon as a student downloads the file. The code is hidden from students and linked to their account. Students can rename the spreadsheet, but the identifying code remains. The code enables the software to identify any part of a student's spreadsheet that comes from another source.

If, for example, a student uploads another student's spreadsheet or copies any part of another student's spreadsheet, the software flags the spreadsheet as suspicious. We classify an assignment as plagiarized only if we can identify the student who originally downloaded the assignment along with the student that uses it. We can only identify the “originator” if they are also registered with the software in any semester. If, however, the student opens another spreadsheet in order to practice or build parts of the assignment and copies that portion into the spreadsheet with the embedded code, then the software also flags the graded spreadsheet as suspicious. Similarly, if a student seeks help from someone not in the system, and if they copy work from this external person’s spreadsheet into their own, or if they pay an external person to build the assigned spreadsheet for them but attach his/her name to this externally constructed spreadsheet, then we can not characterize the work as plagiarized. We do not consider this a major source of mis-classification because the proportion of suspicious spreadsheets in which the originator could not be identified is only 9% of clearly plagiarized submissions.

3.4 Baseline information

We create a standard insert to each Professor’s syllabus that describes the Excel module. The insert explains how to register for the Excel module, the grading system, the availability of tutoring and walk-in workshops for Excel as well as an explicit warning regarding the software’s ability to detect cheating under the heading "Academic Integrity." The text of the insert is as follows:

> **Academic Integrity.** SAM detects files shared with other students and generates a report for the instructors with the names of plagiarizing students and all parties involved. Students caught cheating will be put on a watch list pending further action with their Professor.

In addition to the course syllabus, we also create a course on the learning management system, Blackboard, titled "Spring Excel Module for Finance," for example. We post the syllabus module on the Blackboard course as well. We use the Excel Blackboard course to send all emails to students regarding the Excel module. Thus, from the beginning of the semester all students have access to information regarding the software’s ability to detect plagiarism and the likely consequences if caught.

3.5 First treatment: reminder that plagiarism can be detected

We randomize students evenly into two groups, A and B, within each course. Seven hundred and sixty-four students are in more than one of the four classes. Three hundred and twenty-three of those are in group A in one class and group B in another. We run the analysis with and without students in more than one class and it makes little difference to the results.

Group A receives the warning for the first project via the Excel Blackboard course; Group B serves as the control group for Group A on the first assignment. The script is designed to remind/inform students that the software can detect cheating with explicit sanctions left vague.

> Your next Excel assignment is due next week. As noted on the syllabus, students are expected to do their own work. The SAM system will detect any portion of your project that has been copied from another SAM user. It will also identity the person from whom you copied. Students found using others' work or sharing their own will be put on a watch list pending further action with their course instructor.
>
> The goal is to have you become more proficient in Excel, which is an essential skill in today's workplace. Using another student's work is plagiarism and detrimental to your professional development.
>
> The Excelhelp Team

For the second Excel assignment in each course, Group B, and not Group A, is sent the email above. In this phase, we identify the effect on group B changing status from a control group to a treatment group.

3.6 Treatment 2: the threat of sanctions

After both groups A and B complete the first two assignments, we send an email to all student who have used other students' work as well as to students who share their work. We inform these students in an email that according to the software they have been flagged for using another students's work or having shared their work with other students. We inform them that they are now on a watch list. Any further incidence of plagiarism in the third or fourth assignments will be reported to their professor for disciplinary actions. The script is as follows:

> **Dear SAM Excel User,**
>
> As noted in our previous email to you, the SAM system can detect any portion of your project that has been copied from or shared with another SAM user. The system has flagged one of your assignments as having been copied from or shared with another student. This is a serious violation of academic integrity. Your name has been put on a watch list. Any further evidence of copying or sharing your SAM Excel projects in subsequent assignments will result in notification to your Professor for further disciplinary actions.
>
> The goal is to have you become more proficient in Excel, which is an essential skill in today's workplace. Using another student's work or sharing your work with other students is plagiarism and can have serious consequences for your academic standing and is detrimental to your professional development.

We refer to this notification as the sanction. First, by informing students that they had been caught, we demonstrate the software's capability to detect cheating. We liken this to being arrested and given a warning for a first offense. Second, to be reported to their Professor can carry serious consequences given the Faculty's and the Administration's heightened concern about cheating as more classes are delivered online. We view this as a credible sanction given the likely disciplinary action by faculty and possibly deans.

4 Experimental models

4.1 The effect of a warning

We first estimate the effect of warning students (W) that we can detect plagiarized work on the probability of cheating. The warning is randomized between groups A and B within each course and thus, orthogonal to student characteristics. We estimate the following regression for each class and the first project:

$$c^1_{ijt} = \alpha_0 + \alpha_1 W_i + X_i\alpha + +sect_j + \psi_t + \epsilon_{it}. \tag{2}$$

Let c be the probability that individual i, in section j at time t cheats on the first project as indicated by the superscript. Let W_i be one if the student receives a warning for the project a week before it is due (Group A) and zero otherwise. We include controls for the section and week ($class_j$,ψ_t) that a student submits a project and student characteristics (X_i) as listed in Table 1.[4] The due dates for projects vary by course. This is relevant because some students are enrolled in more than one of the four courses. A student in the Finance course, which has the earliest due date for the first assignment, may receive a warning because she is in Group A, but then does not receive a warning for her first Management project because she is in Group B. Such mis-classification can attenuate differences in the effect of warnings in courses with due dates after those in Finance. The experiment in Finance, therefore, is uncontaminated by this source of mis-classification, especially for the first assignment. This is potentially less true in the other courses. As we show, being in multiple SAM sections is balanced across treatment assignment. We also show that our results are unaffected if we exclude all students who were in multiple classes.

[4]In another set of regressions we pool projects one and two for each class and control for student and project fixed effects. For students in Group A the warning variable equals one for projects one and two but is one for Group B only for project two.

4.2 The effect of a sanction

The second effect we estimate is the probability that students cheat on a third assignment given they are caught cheating on the first or second assignment. We describe this as a sanction because it is analogous to being arrested and given a first warning about their behavior. We use the timing of the sanction to identify its effect on subsequent cheating. Specifically, sanctions are not randomly assigned but delivered to everyone that has been caught cheating on the first or second project a few days after the second project is due. However, students can submit their assignments at any point prior to the due date. Roughly half the students who cheat on the first or second assignment submit their third assignment before receiving a sanction. Thus, we estimate the effect of the sanction by the difference in the probability of cheating on the third project between cheaters who receive the sanction before as opposed to after submitting the third assignment.

$$c_{ij}^{3} = \beta_0 + \beta_1 Sb_i + \beta_2 Sa_i + \beta_3 W_i + X_i\beta + sect_j + \epsilon_i. \tag{3}$$

The dependent variable is an indicator of whether a student in section j cheated on the third assignment and zero otherwise. Let Sb be one if the student is sanctioned before submission of the third project and zero otherwise; let Sa be one if the student is sanctioned after submitting the third assignment; W is a dichotomous indicator for students in Group A who are not flagged for cheating on any previous assignment; the reference category is students in Group B who are not flagged for any previous assignment.[5] We estimate the effect of sanctions as the difference in cheating behavior between Sb and Sa or $\beta_1 - \beta_2$. We do not include time fixed effects in this regression because it would be perfectly collinear with Sa and Sb. The identifying assumption is that the timing of the submission of the third assignment is unrelated to a student's proclivity to cheat on the first or second project.

We can however relax this assumption and allow the proclivity to cheat on the first two assign-

[5]Since students could be in multiple classes, students who cheated in any class on their first two projects and were sanctioned prior to submission of the third project are counted as being in group Sb. Similarly, students that cheated in any class on their first two projects and are sanctioned after submission of the third project are counted as being in group Sa.

ments to vary by when a student is sanctioned.

$$c_{ij}^{p} = \beta_0+\beta_1 Sb_i^3+\beta_2 Sa_i^3+\beta_3 W_{it}^3+\theta_1 Sb_i^{(1,2)}+\theta_2 Sa_i^{(1,2)}+\theta_3 W_i^{(1,2)}+X_i\beta+third_p+sect_j+\epsilon_i. \quad (4)$$

Here we pool data from the first three projects and control for the mean cheat rate on project three ($third_p$). The dependent variable, c_{ij}^{p} is one if a student in section j cheats on project p (p=1,2,3). As in equation (3) Sb_i^3 and Sa_i^3 equal one if student i is sanctioned before or after submission of the third project. We now include interactions of the sanctioned students with an indicator of project 1 or 2 ($Sb_i^{(1,2)}$). θ_1 estimates the mean cheat rate on the first two projects among students who are sanctioned before they submit their third project and θ_2 estimates the same among students who are sanctioned after they submit their third project. The difference, $\theta_1 - \theta_2$, captures the differential proclivity to cheat on the first two projects among students sanctioned before and after submission of the third project. The difference-in-differences estimate [($\beta_1 - \beta_2$)-($\theta_1 - \theta_2$)] removes the time-invariant proclivity to cheat between students sanctioned before or after submission of the third project.

5 Experimental results

5.1 Balance

All students who register for one of the four classes are randomized between two groups within each of four courses. The first two columns in Table 1 show the mean characteristics by assignment to group A or group B and the third column presents the standardized differences. A joint test of whether student characteristics predict group assignment yields a joint χ^2 p-value of 0.86. The last three columns show the means and standardized differences for the subset of students that did at least one Excel project. There is no loss of balance between groups A and B in this subset of students. Subsequent analyses only include the subset of students who completed an Excel assignment.

5.2 Warnings

The results of the experiment are well described by Figure 2-4. In each we show the cumulative proportion of assignments flagged for cheating (the cheat rate) for each project in each course by week of the semester. The vertical axis shows the cumulative proportion of assignments of all assignments eventually submitted flagged for cheating. The broken vertical line marks the week the warnings are sent out and weeks with asterisks mark the assignment due date. The results for the Finance course are shown in Figure 2. [6] The cumulative cheat rate for Group A is the solid line and Group B is the broken line. Almost two percent of assignments are flagged for cheating prior to the warning sent to Group A in Finance. Between the warning and the due date the proportion of assignments flagged for cheating increases to about eight percent. Cheating continues after the first assignment due date and peaks at approximately ten percent.[7] The important takeaway from the first panel of Figure 2 is the lack of any substantive difference in the proportion of flagged assignments between Groups A and B. The warning about our ability to detect cheating has no deterrent effect.

The same pattern persists for the second Finance project in which Group B is warned and A is not (Figure 2, panel 2). The proportion of flagged assignments increases from two to almost ten percent by the due date and again there is no difference in the proportion of flagged assignments between Groups A and B.

We formalize the lack of an effect of the warnings on cheating in Table 2 Panel A for single course students. Estimates are from the linear probability model of equation (2) above. The coefficient on "Warned prior to due date" in the first column shows that cheating is 1.2 percentage points greater in the group that is warned (Group A) relative to those who are not warned. The

[6] We focus on Finance because its project was due earliest in the semester. Recall some students were in more than one of the four courses. A student in Finance and Management, for example, whose first project in Management was due after Finance's first project may have received a warning in Finance and altered her behavior or she may have warned other students in Management about the software's ability to detect cheating. This source of contamination was not an issue for the first project in Finance.

[7] Recall students can submit assignments after the due date and still receive full credit if their score after the penalty for lateness exceeds 80 percent.

change was in the opposite direction of a deterrent effect and much smaller than its standard error. Column (2) shows that there is again little difference in cheating between groups A and B when the latter group is warned prior to the second Finance project. This results are not much different when students from multi-course sections are included in column (1) and column (2) of Panel B. Although the deterrence effect of warning is in the expected direction, once again standard errors are larger than effect sizes.

5.3 Sanctions

One week after the second assignment is due, students flagged for cheating are sent an email indicating that their assignment contains material from another student or their work is used by another student. All are informed that they have been put on a watch list and that any subsequent violations of academic integrity will involve their instructor pending further action. [8]

The sanctions have immediate effects on the cheat rate in the third assignment in Finance (Figure 2, panel 3). The proportion of third assignments flagged for cheating falls by roughly half and declines to approximately two percent by the fourth assignment (Figure 2, panel 4).

The impact of sanctions on cheating is actually larger than indicated by Figure 2. Fifty-seven percent of students who cheat on either the first or second project submit their third project before being sanctioned. Thus, only those who are sanctioned prior to the submission of the third project are actually exposed to the treatment. In Table 3 we show results from the estimation of equation (3). The dependent variable is one if they cheat on the third project and zero otherwise. The coefficients are the percentage point changes in the probability of cheating on the third assignment relative to students in Group B who did not cheat on any assignment. Compared to group B, seven percentage points greater students who cheated on either of the first two assignments and who are

[8] Some students protested that they had not used work from someone else. In such cases we sent them the name of the person they copied from. Often this provided sufficient evidence. Some students did not recognize the name of the sender. In many such cases one student's spreadsheet had been shared with numerous students. Similarly some students whose spreadsheet had been submitted by multiple users argued that they had only shared their work with a friend who was struggling and could not be blamed for its use by multiple students. In all cases, students remained on the watch list but we treated these exchanges as teachable moments.

sanctioned before they submit the third assignment cheat on the third assignment as compared to 40.3 percentage points greater of previous cheaters who are sanctioned after they submit the third assignment. This represents a drop of 33.3 percentage points. Estimating the difference in differences the effect is a 42.9 percentage point decline, a relative decline of 91.5 percent compared to a mean cheat rate of 46.9 percent on the first two projects.

5.4 Cheating in the other courses

The pattern of cheating in the other courses is similar to that observed in Finance although the rate of cheating varies substantially. Over ten percent of students in Management cheat on the first project (Figure 3). The rate of cheating grows to 19 percent on the second project (Figure 3). Again there is no difference in cheating between groups A and B for either project. After sanctions, cheating falls by more than half. The rate of cheating in the two Accounting courses is much lower than in Finance or Management, but the pattern remains the same: cheating falls precipitously after sanctions are imposed (Figures 4 and 5).

The regression results for Management and all four courses combined confirm the pattern. The second column of Table 3 shows the impact of sanctions on the rate of cheating on the third project in Management. Cheating is 55.4 percentage points less among Management students who are sanctioned after they submit their third project compared to those who submit their project before being sanctioned. The difference in differences estimate is a 39.1 percentage point decline for a relative decline of 82.1 percent (39.1/47.6). The difference-in-difference decline in cheating on the third project across all four courses is 35.7 percentage points or 87.8 percent (35.7/43.4) relative to previous project cheating means.

The consistent finding across all four courses is that email warnings have no effect on cheating whereas identifying cheaters and putting them at risk for disciplinary action have dramatic effects. The consistency of the results also suggests that even students in more than one of the four courses who may receive two or more warnings were unaffected. What we don't know from these findings is the extent of interactions among students. Do students in Group A communicate to others the lack of any sanction after the first project? Does word of the sanctions after project 2 spread quickly among students? In the next section we explore possible peer effects.

6 Peer Effects

Our experiment assumes that warnings regarding cheating and sanctions of those who were caught only affects students who receive them. This is known as the Stable Unit Treatment Value Assumption (SUTVA). In other words, we assume no peer or spillover effects. This is an unrealistic assumption as cheating in this context involves interactions among students.

Manski (1993) describes three types of peer effects: endogenous peer effects occur when student (i) is affected by the rate of cheating among some grouping of students to which student (i) is exposed. Unbiased estimates of endogenous peer effects are extremely challenging to uncover statistically as every individual student is both an outcome and part of the treatment (Angrist, 2014).

By contrast, contextual or exogenous peer effects are obtained by regressing the probability that student (i) cheats on the predetermined characteristics of the putative peer group. Carrell et al. (2008) use self-reported cheating in high school as an exogenous determinant of cheating in college. Sacerdote (2001) uses the SAT score of a randomly assigned college roommate on the other roommate's freshman GPA; Glaeser et al. (2003) use the proportion of students in one's dormitory at Dartmouth who drank in high school to explain the likelihood that a student will join a fraternity. Random assignment of roommates insures that estimates of exogenous peer effects are not contaminated by deliberate grouping among students (Sacerdote, 2001; Carrell et al., 2008, 2013).

The Finance and Management courses had 12 and 16 sections, respectively, of approximately 80 students per section. We begin our exploration of spillover effects by using course sections as the relevant peer group. Students, however, are not randomly assigned to sections and may chose them to be with friends. Thus, we lack the exogenous formation of groupings as in previous studies (Sacerdote, 2001; Carrell et al., 2008, 2013). Nevertheless, cheating involves interactions among students that may be facilitated by attending the same section of a course. Based on a sub-sample of data, we know that 55.6 percent of plagiarized files are obtained from someone in the same course section. [9] A randomized sorting of plagiarizing students to originators would result in only 11.5 percent of plagiarized files coming from someone in the same section. Thus, the course section offers a plausible grouping from which to explore possible peer effects.

We focus on the second project in each class and asked whether the probability that student (i) in section (j) cheats on the second project (t) (c^2_{ijt}) is affected by the proportion of the student's classmates (j(-i)) in section (j) who cheat on the first project ($\bar{c}^1_{(-i)j1}$). [10]

$$c^2_{ijt} = \gamma_0 + \gamma_1 c^1_{ij} + \gamma_2 \bar{c}^1_{(-i)j} + X_i\Gamma + \psi_t + \mu_{ijt}. \quad (5)$$

Equation (3) captures the linear-in-means spillover effects adjusted for individual characteristics (X_i) and for a student's own cheating on the first project (c^1_{ij}). As Angrist (2014) notes, $\bar{c}^1_{(-i)j}$ is best interpreted as a jackknife instrumental variable estimate in which the first stage is individual cheating outcomes on the first project regressed on dummies for the section of each class. However, a weak first-stage based on many groups will tend to yield equality between OLS estimate and two-stage least squares estimates.[11]

The results are shown in table 4. A student who cheats on the first project is 60 to 65 percentage points more likely to cheat on the second project relative to students who do not cheat on the first project (Table 4 Panel A, columns (1), (4) and (7). Similarly, in columns (2), (5), and (8) we present the effect of the leave-one-out mean cheat rate of the first project on an individual's likelihood of cheating on the second project. The group effect differs little from the effect of own cheating, a result consistent with Angrist's (2014) suggestion of a weak first stage. Indeed, the partial R^2 on the set of course section dummies in the first stage is never greater than 0.04 (Table 4, Panel A).

[9] Recall that we know the originator (i.e. the person who downloaded the plagiarized file originally) and receiver of plagiarized assignments. However, not all senders took the class in the same semester as the receivers and thus we lack detail data on all originators.

[10] We suppress the class (k) subscript as j is a subset of k.

[11] In our context, the OLS estimate is $c^2_{ijt} = \gamma_0 + \gamma_1 c^1_{ij} + X_i\Gamma + \psi_t + \nu_{ijt}$ or cheating on project 2 regressed on an individual's cheating on project 1 while the approximate 2SLS would substitute the group cheating on project 1 for the individual cheating, $c^1_{ij} = \eta_0 + \eta_1 \bar{c}^1_{(-i)j} + X_i\Gamma + \nu_{ijt}$.

Controlling for both own cheating and group cheating decreases the estimated peer effect by one third to a half (Table 4 Panel A, columns (3), (6) and (9).

As further exploration of peer effects, we estimate equation (3) for the third project and used own and the section cheating rate on the second project as regressors (Table 4, Panel B). The results in table 4 Panel B shows the diminished effect of own cheating in comparison to previous projects ranging from 27-35 points. This reflects a combination of students who submit their project before sanctions and thus are untreated and students who submit projects after being sanctioned and thus drastically curtail their cheating as a result of sanctions. The estimated group effects, however, are much smaller than the effect of own cheating and flip sign and become statistically insignificant when included with own cheating (Table 4 Panel B, columns (3), (6) and (9)).

In the end, we can not rule out significant peer effects. Sharing work with other students involves interactions. However, we remain skeptical that the coefficient on the mean cheat rate captures a causal peer effect distinct from or in addition to a student's own propensity to cheat. From an administrative perspective, the separate identification of individual from peer effects may be irrelevant to the goal of reducing cheating. The more unambiguous result is that appeals to academic integrity unsupported by credible identification of plagiarism are ineffective at curbing cheating in this context.

7 Epilogue

The experiment was conducted during the spring semester of 2019. This was the first time students who plagiarized were identified and placed on a watch list. In subsequent semesters, we continued to warn students about the software's ability to identify work that was not their own. We persisted in identifying students who cheated and informing them that subsequent transgressions would involve their Professor. Figure 6 shows the cheat rate on first project by semester and course beginning in the fall of 2016. The cheat rates were prior to any identification and sanctioning of cheaters in the semesters following the experiment. In Finance and Management the rate of cheating after the spring of 2019 was 80 to 90 percent lower than levels reported in the experiment. Given the complete lack of an effect of warnings in the experiment, we suspect that subsequent warnings were viewed as more credible based on the experience of students in the spring of 2019. Many students from the experimental semester continued to learn Excel through the online module when taking any of the other four required business courses in subsequent semesters.

8 Conclusion

We test whether randomly delivered email warnings to college students about our ability to detect plagiarized work deters cheating. We contrast the effect of warnings with the threat of more serious disciplinary actions for students caught submitting work of other students. We find that randomly assigned warnings do not deter cheating. Only when we demonstrate our ability to detect cheating and notify students that they are on a watch list for subsequent assignments does cheating fall dramatically. The takeaways appear clear: boilerplate messaging in syllabi regarding academic integrity are largely ignored. Even email messages delivered a week before an assignment is due are ineffective. Not until students are caught and at risk for serious disciplinary action does cheating decline on subsequent work.

Our study is unique. The software students use to submit and grade assignments is highly sensitive: there are few if any false positives. The software's specificity is less robust: if students copy material from another student or person who is not registered in the system at this college, then we do not accuse them of cheating. Approximately nine percent of suspicious submissions may be false negatives.

Another limitation is the likely presence of peer effects. Our definition of cheating requires some form of sharing between students. We are able to show with a sub-sample of data that students who share their work with others are more likely to be in the same section of a course than if sharing had been random. Despite these apparent networks effects, we cannot separately identify peer effects from own propensities to cheat.

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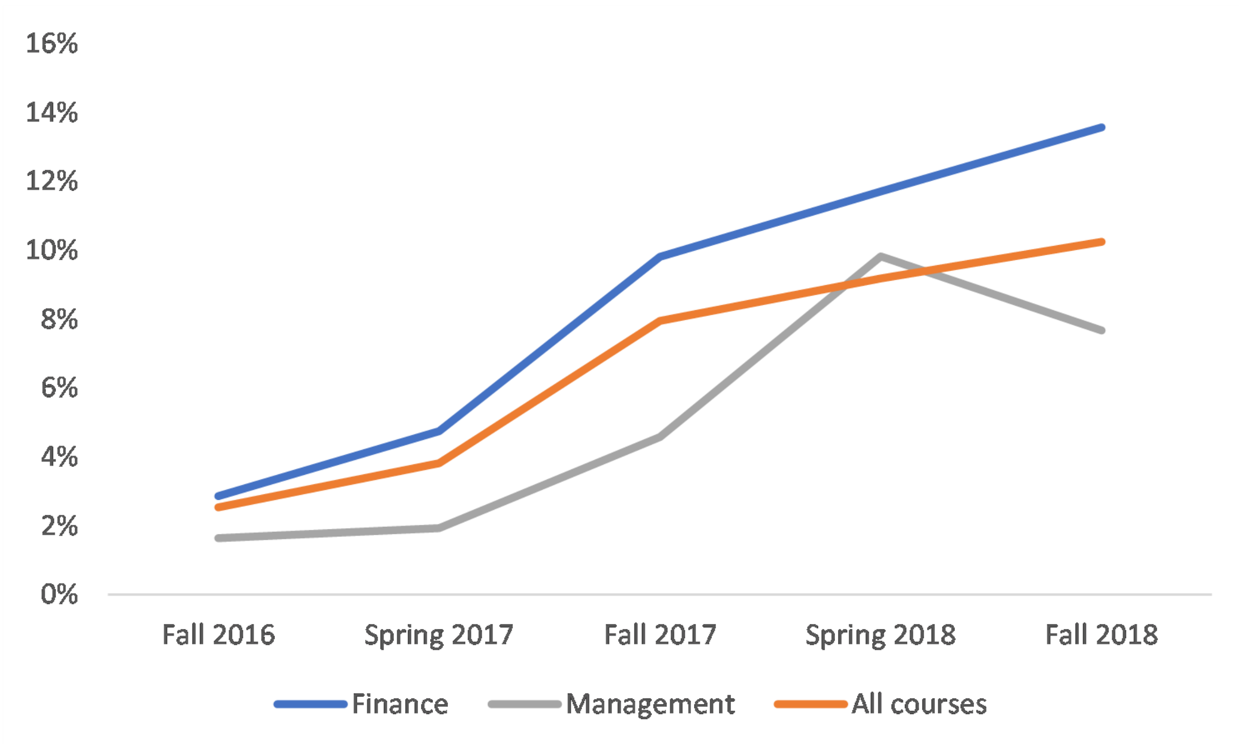

Figure 1: Percent of students that plagiarized on the first project by course and semester prior to the experiment

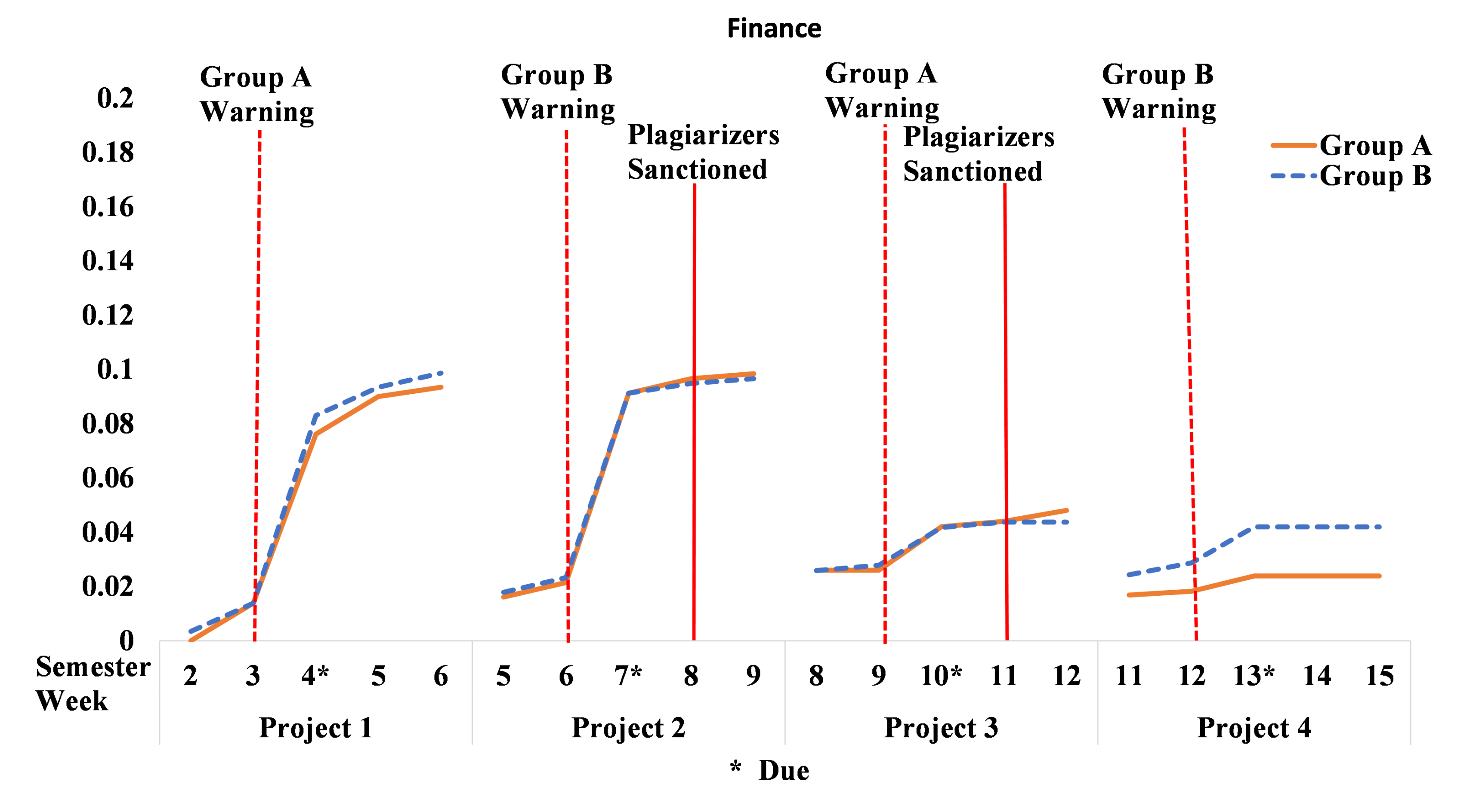

Figure 2: Cumulative cheating rate in the Finance course by project and week of semester

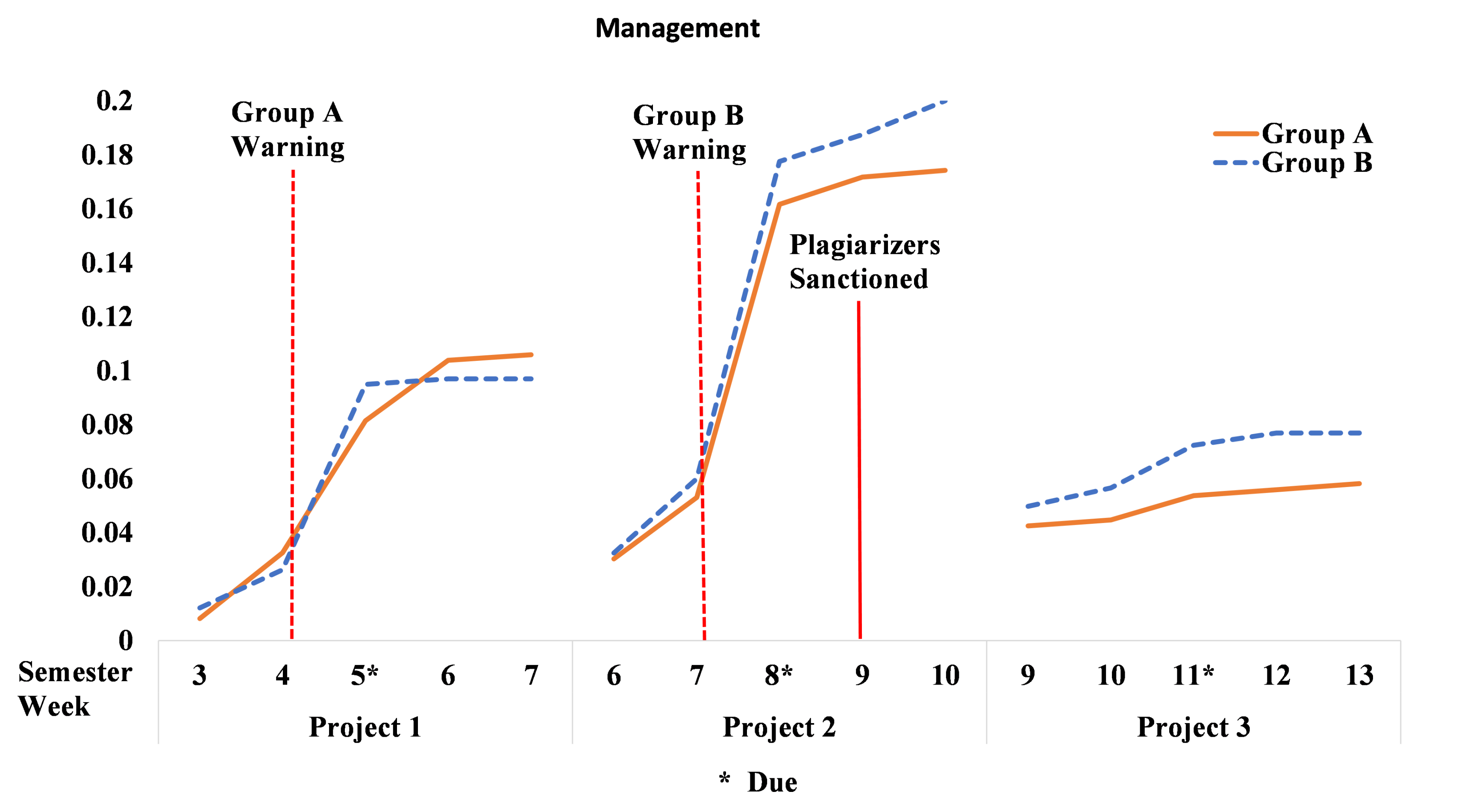

Figure 3: Cumulative cheating rate in the Management course by project and week of semester

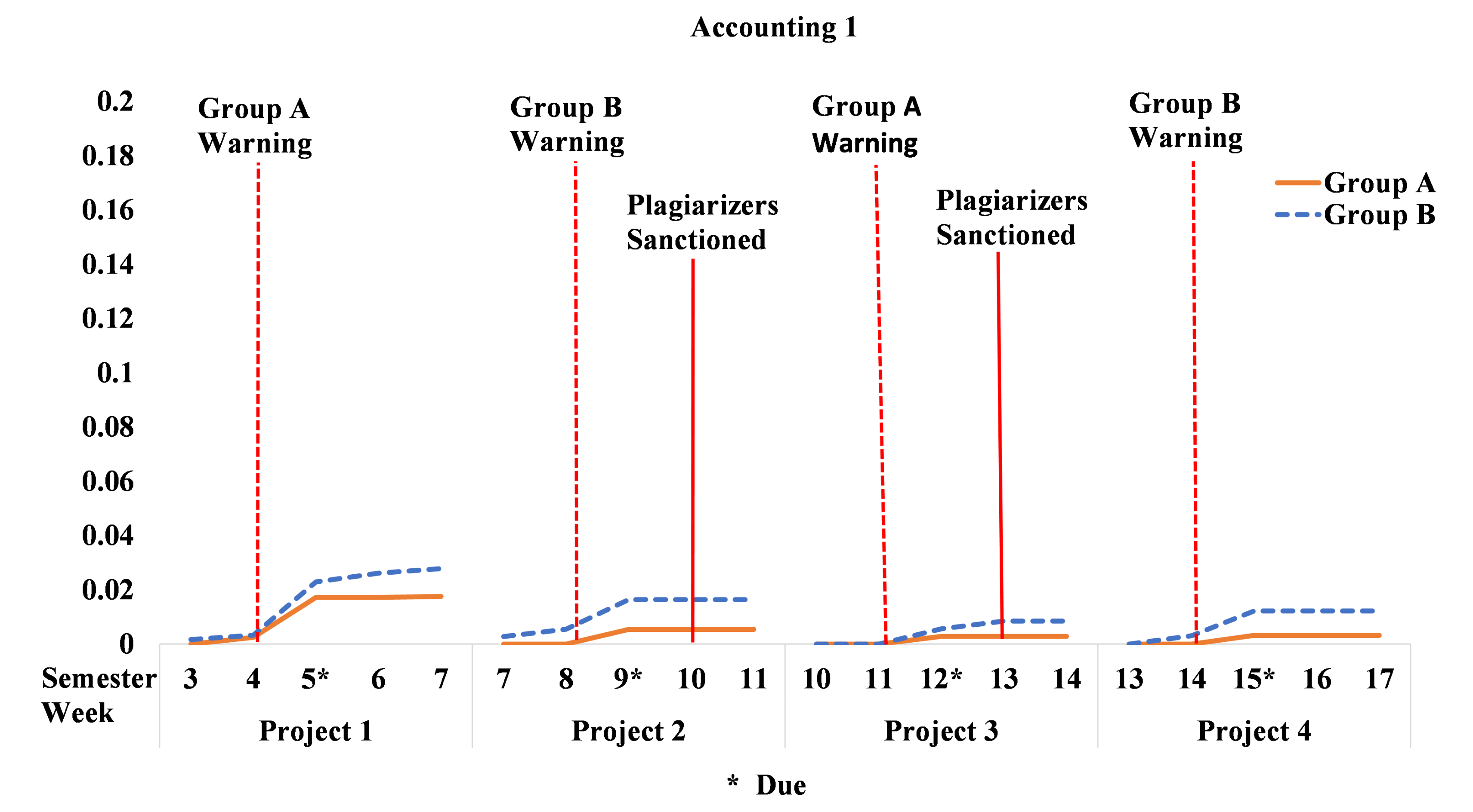

Figure 4: Cumulative cheating rate in the Accounting 1 course by project and week of semester

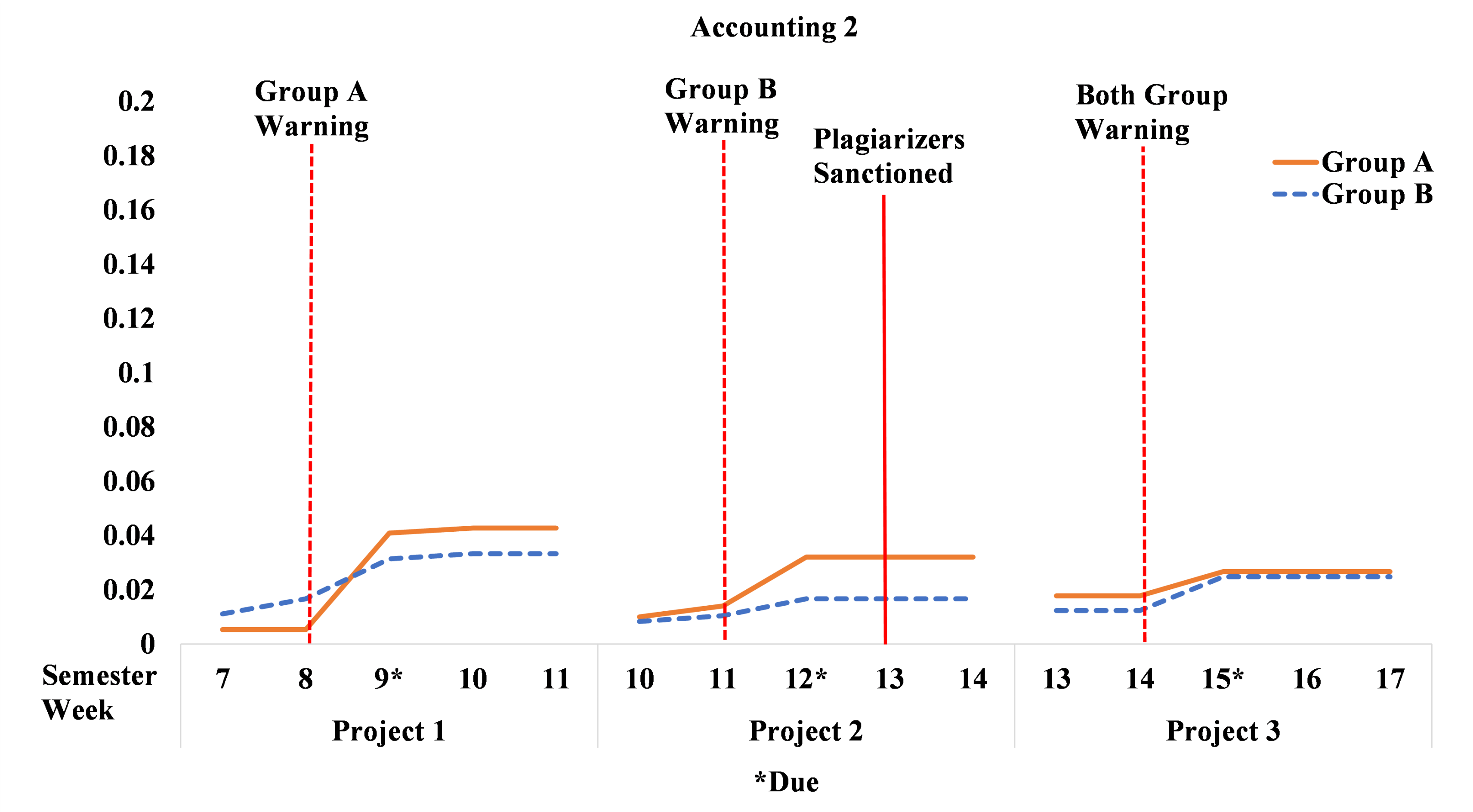

Figure 5: Cumulative cheating rate in the Accounting 2 course by project and week of semester

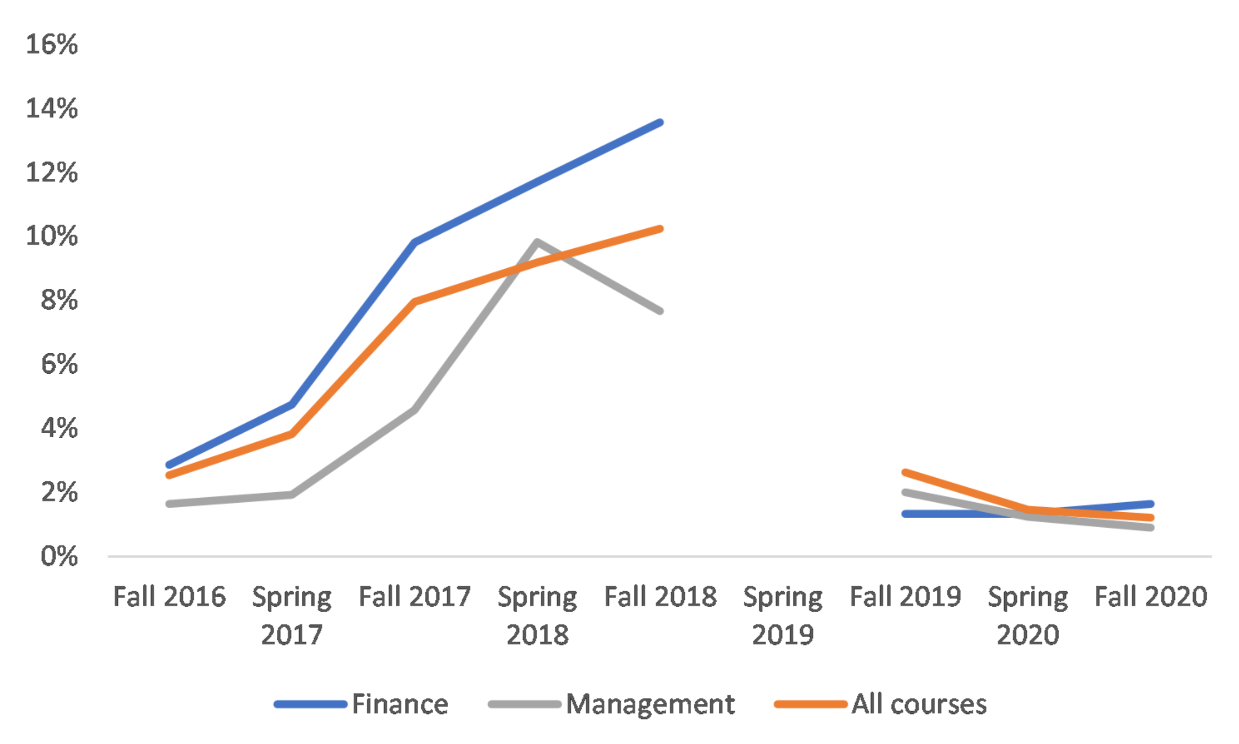

Figure 6: Percent of students that plagiarized on the first project by course and semester before and after the experiment

Table 1: Characteristics by randomization group[1]

	Randomized			Completed SAM Assignment		
	Group A	Group B	|Diff/S.D.|	Group A	Group B	|Diff/S.D.|
Prior School Performance						
GPA	3.1	3.1	0.00	3.2	3.2	0.00
SAT Verbal	526.0	526.4	0.00	526.9	527.3	0.00
SAT Math	586.7	586.4	0.00	590.6	588.5	0.00
School Experience						
Cumulative Credits	30.9	30.7	0.01	30.2	30.4	0.01
Underclass (%)	68.8	69.1	0.01	70.2	69.7	0.01
Attends Part Time (%)	10.2	10.9	0.02	9.6	9.2	0.01
Multiple Exp. Courses(%)[2]	46.4	46.9	0.01	46.4	46.9	0.01
Completed SAM Assignment	87.4	85.6	0.05	100.0	100.0	0.00
Demographics						
Age	21.9	21.9	0.00	21.8	21.8	0.02
Female (%)	44.0	44.5	0.02	45.6	46.4	0.02
Native English Speaker (%)	50.8	52.4	0.03	50.0	51.3	0.03
Race/Ethnicity						
Asian (%)	46.7	44.5	0.04	47.9	46.3	0.03
Black (%)	9.9	11.3	0.05	9.4	11.3	0.06
Hispanic (%)	20.9	21.0	0.00	19.9	20.4	0.01
White (%)	19.9	20.1	0.00	20.6	19.5	0.03
Other (%)	2.4	2.8	0.03	2.2	2.6	0.03
# of Observations[3]	2,166	2,168		1,893	1,855	
# of Students	1,947	1,941		1,703	1,671	
Joint χ^2 p-value[4]		0.857			0.963	

[1] Columns under the subheading "Randomized" include all students that were randomized at the beginning of the semester. Columns under the subheading "Completed SAM Assignment" include only those students that completed at least one assignment in SAM.
[2] Multiple Exp. Courses (%) refers to the percentage of students that are in more than one experimental course.
[3] Students are included multiple times for each course in which they were enrolled.
[4] Joint χ^2 p-value is obtained from a joint test of the coefficients in a logistic regression that includes an indicator for group assignment as the dependent variable and the characteristics with group means imputed for missing characteristics and indicators for missing characteristics as the independent variables.

Table 2: Effect of assignment to warning prior to due date that the software can detect plagiarized work on cheating by course and project.[1,2,3]

	Finance		Management		All Courses	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	1st proj.	**1st & 2nd proj.**	**1st proj.**	**1st & 2nd proj.**	**1st proj.**	**1st & 2nd proj.**
Panel A: Single course students[4]						
Warned prior due date	1.2	1.5	2.9	1.0	0.7	0.3
	(2.8)	(3.2)	(3.1)	(5.6)	(1.2)	(1.7)
Mean Cheat Rate	9.8	9.0	12.8	17.4	7.6	8.1
# of Obs	528	1,037	492	904	1,955	3,757
# of Students	528	535	492	495	1,955	1,987
Panel B: Single and multi course students[5]						
Warned prior to due date	-1.4	-0.6	0.2	2.7	-0.5	-0.5
	(1.8)	(2.1)	(2.2)	(3.9)	(0.9)	(1.1)
Mean Cheat Rate	10.4	10.3	10.8	14.6	7.6	8.2
# of Obs	1,131	2,232	986	1,782	3,670	7,010
# of Students	1,131	1,151	986	991	2,988	3,029

[1] Estimates are from a linear probability model and measured in percentage points. Warned prior to submission equals 1 if students received an email message warning them of the software's ability to detect cheating prior to the project's due date. Significance levels of differences are indicated by $* \, p < .05$.
[2] Column (1), (3), and (5) shows the effect for the first project where only group A students had received the warning prior to the due date. These are reduced form effects since some may have submitted prior to the warning. Section fixed effects and characteristics are controlled in these models.
[3] Column (2), (4), and (6) shows the effect of group B moving from being a control to a treated group while group A stays a treated group. Student and project fixed effects are included and results are clustered at the student level.
[4] Panel A includes only students that are enrolled in a single SAM section during the experimental semester since they would be uncontaminated by warnings from other classes.
[5] Panel B includes all students even though multi course students may be randomized into group A in one course and group B in another course. Estimates are still technically valid since randomization in each course is orthogonal to randomization in all other courses but the complier group is a smaller fraction than in panel A.

Table 3: Effect of sanctions on probability of cheating on the third project by course.[1,2]

	Fin.		Mgt.		All Courses	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Sanctioned before submission (β_1)[3]	7.0*	5.7*	5.0*	3.6*	5.4*	4.6*
	(1.9)	(1.5)	(2.0)	(2.3)	(1.5)	(1.5)
Sanctioned after submission (β_2)[4]	40.3*	41.9*	60.4*	65.2*	51.9*	53.4*
	(3.3)	(7.3)	(3.8)	(6.8)	(4.5)	(4.8)
Group A unsanctioned (β_3)	0.7	0.6	-1.5	-1.2	-0.3	-0.5
	(1.9)	(1.0)	(1.8)	(1.3)	(0.4)	(0.5)
Difference in third project cheat rate (β_1- β_2)[5]	-33.3*	-36.2*	-55.4*	-61.5*	-46.5*	-48.8*
	(3.6)	(7.8)	(4.1)	(7.1)	(4.9)	(4.9)
Difference of prior cheat rate (θ_1- θ_2)		6.7*		-22.4*		-10.8*
		(2.7)		(2.9)		(4.7)
Difference-in-differences [(β_1-β_2)-(θ_1- θ_2)][6]		-42.9*		-39.1*		-38.1*
		(4.8)		(5.1)		(4.1)
Cheat rate of unsanctioned group B students	1.5	1.5	3.3	3.3	1.7	1.7
Prior cheat rate among sanctioned	46.9	46.9	47.6	47.6	43.4	43.4
# of Obs	1,003	2,992	889	2,541	3,257	9,564
# of Students	1,003	1,003	889	889	2,669	2,669

[1] Estimates for odd columns are of equation (3) in the text and obtained from a linear probability model. Effects are reported as percentage points. The reference category includes students in group B who were not sanctioned on project 1 project 2. Estimates are adjusted for covariates from table 2 and standard errors adjust for general Huber-White type heteroskedasticity or are clustered by student for column (5). Significance levels of differences are indicated by $* \ p < .05$.

[2] Estimates for even columns are difference-in-differences estimates for the effect of sanctions that include the first and second projects in the regression and account for the possibility that those that submit projects before and after sanction may have different average cheat rates.

[3] *Sanctioned before submission* is 1 if a student plagiarized a prior project and was sanctioned one week prior to their submission of the third project, due one week after sanctions went out.

[4] *Sanctioned after submission* is one if a student plagiarized a prior project but submitted the third project before being sanctioned.

[5] β_1- β_2 is the effect of sanctions on the probability of plagiarism on the third project among those who were sanctioned on prior projects if there are no differences between those sanctioned before and after submission of third project in average cheat rates.

[6] *[(β_1-β_2)-(θ_1- θ_2)]* is the effect of sanctions on the probability of plagiarism on the third project among those who plagiarized prior projects if the difference between those that were sanctioned before the third project and those that were sanctioned after would have remained constant if not for the sanction.

Table 4: Probability of cheating on project given prior project own cheating and mean peer cheating by course[1]

	Finance			Management			All Courses		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Panel A: Peer effects on project 2[2]									
Own cheat proj. 1	64.6*		63.5*	61.2*		60.5*	60.4*		59.5*
	(5.4)		(5.1)	(5.5)		(5.5)	(3.8)		(3.7)
Sect. mean cheat proj. 1		73.0*	38.9*		87.4*	70.2*		78.0*	52.7*
		(13.0)	(10.0)		(37.0)	(33.2)		(12.4)	(11.7)
Sect. Partial R^2		0.037			0.033			0.030	
# of Obs		1,081			791			3,282	
Panel B: Peer effects on project 3[3]									
Own cheat proj. 2	27.6*		27.9*	34.8*		35.2*	34.2*		34.6*
	(5.0)		(5.0)	(3.7)		(3.5)	(3.3)		(3.3)
Sect. mean cheat proj. 2		11.6	-6.7		7.9	-11.3		12.0	-9.1
		(7.1)	(7.6)		(8.6)	(9.8)		(5.2)	(6.1)
Sect. Partial R^2		0.056			0.065			0.055	
# of Obs		997			770			3,100	

[1] Estimates are of equation (4) in the text and obtained from from a linear probability model. Effects are reported as percentage points. Estimates are adjusted for covariates in Table 1. Group cheating rates are the the number of students who cheated on the immediately prior project in section (j) of course (k) less student (i) divided by the number of students in section (j) of course (k) less student (i). Sect. Partial R^2 refers to the additional variation explained by section fixed effects out of variation leftover after controlling for student fixed effects. Standard errors are adjusted for a general form of heteroskedasticity. Significance levels of differences are indicated by $* \; p < .05$.

[2] Panel A looks at the effect that own and peer cheating from project 1 has on whether students cheat on project 2, which was due before any sanctions were sent out.

[3] Panel B looks at the effect that own and peer cheating on project 2 has on students on project 3, which was due after sanctions were sent out.