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The Salience of Remote Friendship: Quasi-experimental Evidence When Instruction Goes Virtual

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Abstract: What are remote friends for? Unanticipated campus closures during COVID19 created uneven student-level exposures to virtual learning challenges, and physically separated campus friends. Using university administrative data, and exogenous class-level differences in pre-pandemic on-campus housing assignments for parallel trend validation, this paper unpacks student-by-course variations in grade expectations using within-semester switches in grade option choice as cues. We find causal evidence that pandemic learning challenges encouraged Satisfactory/Unsatisfactory grade-option uptake among freshmen, but having at least one (remote) friend in class nullified the effect. We explore evidence consistent with performance-improving mutual support despite physical distance between friends as underlying mechanism.

JEL Classification: I20, I29
Keywords: Remote Friendship, Satisfactory/Unsatisfactory Grade Option, COVID19, Distance Education, Learning Outcomes.

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1 Introduction

What difference does having a remote peer in class make in virtual instruction environments? Studies have long confirmed the importance of friendship as a source of peer support in in-person instruction settings (e.g., Hoxby, 2000; Sacerdote, 2014; Calvó-Armengol et al., 2009; Isphording and Zölitz, 2020; Getik and Meier, 2024). However, the role of remote friendship with fellow classmates in mitigating learning challenges associated with online instruction has not been explored, even as virtual education programs have become norms rather than exceptions.[2] Do virtual instruction environments dilute the salience of (remote) friendship support, or do they instead underscore its importance?

In this study, we use the unanticipated separation of existing peer networks as a result of COVID-19 campus closures to determine whether remote friendship matters in online distance learning settings. Using administrative data covering over 12,000 undergraduate students at Cornell University, a university located in the city of Ithaca in upstate New York, we assess how students' grade-performance expectations changed from before the pandemic to the last day of the Spring 2020 semester depending on prior friendship links with other students in the same remote classroom. The data offer a daily view of the student records, along with information to appraise the strength of a student's acquaintance network in any given course. We take a student-centric approach to measuring grade performance expectations by presenting a causal study of grade option choices (Graded or Satisfactory/Unsatisfactory, henceforth S/U) before, during and after the return home order depending on access to friendship support in the virtual classroom.

Many prior studies have assessed the impact of distance education on learning outcomes, a small number of which are related to the COVID19 setting.[3] The key research challenges are two-fold. First, students self-select into distance learning programs, and thus the underlying causes of enrollment may coincide with grade sensitive factors (e.g. degree of preparation). Second, while instructor-assessed outcomes such as grades have been more widely studied (e.g., Figlio et al., 2013; Bowen et al., 2014), it is not always straightforward to assess sources of learning difficulties

[2]For example, in the 2022-23 academic year in the United States, about 53% of post-secondary students were enrolled in at least one online course U.S. Department of Education, National Center for Education Statistics (2024).

[3]A number of recent studies assess the role of online instruction on learning outcomes in general (e.g., Altindag et al., 2021; Kofoed et al., 2021; Bettinger et al., 2017; Alpert et al., 2016). Specifically related to COVID19, Aucejo et al. (2020),Barnum and Bryan (2020), Jaeger et al. (2021) and Rodriguez-Planas (2022) rely on student survey data, while Ozsoy and Rodriguez-Planas (2023), Rodríguez-Planas (2022), and Bird et al. (2022) address the impact of online learning on academic performance using administrative data sets. We discuss these studies in detail in relation to our work in Section 2.

using posted grades and learning assessments. For example, teacher-assessed grade outcomes may embody grade adjustments (e.g., grade inflation) depending on individual and class circumstances, while the scope and depth of materials covered may also have varied precisely when remote learning presents instruction challenges.[4]

This paper circumvents the first identification challenge by leveraging the unanticipated change in the mode and location of learning after the national emergency declaration in March 2020 in the United States due to COVID19 (U.S. Department of Education, 2021).[5] The return home order generated rich student-level heterogeneity in exposure to the challenges of online learning (e.g. distance from campus and internet access). We will refer to distance from campus and internet coverage associated with a student's home address as two continuous student-level dimensions of a return home treatment.[6]

Next, to allay concerns that teacher-assessed course grades may embody student-, class-, and / or instructor-specific adjustments and accommodations in a pandemic, we use student-course-level grade option choice (Graded or S/U) responses to the return home order as a self-assessed measure of course performance expectations from before the pandemic until the end of the semester. Research on the pros and cons of flexible grading options has a long tradition in education research (Marshall, 1973), but empirical studies are very rare and there have been no theoretical studies to guide hypotheses / empirical models.

From a pedagogical perspective, the S/U option encourages students to take challenging courses, fosters exploration of new subject matter, mitigates grade competition (Mclaughlin et al., 1972; Bain et al., 1973), and reduces stress and anxiety (Marshall, 1973). The latter was a key consideration for college administrations at the start of the COVID19 pandemic (Basken, 2020; Venable, 2020). At Cornell University, for example, 1 in 6 (13.5%) out of all student-course level observations are S/U during the pre-pandemic semester of Spring 2019. This doubled to 27.5% during the spring 2020 pandemic semester, where the majority of S/U switches took place during the last weeks of the semester.

From the perspective of students who care about grades, the S/U option allows users to avoid

[4]For example, grade inflation during the Spring 2020 semester is reportedly widespread (Rodríguez-Planas, 2022; Altindag et al., 2021). We find the same tendency of grade inflation in our study setting as well in the Spring 2020 semester.

[5]According to U.S. Department of Education (2021), over 84% of undergraduate students in the United States saw some or all of their in-person classes moved to online only.

[6]We also control for exposure to COVID, using a COVID exposure index that measures COVID exposure risks derived from cell-phone traffic data (Couture et al., 2022).

a grade penalty when they expect to underperform in a class (Marshall, 1973). Thus, observed S/U option choices can be seen as a student-assessed indicator of expected grade performance by revealed preference. We find that this reasoning can be more formally established in an extension of the Becker and Rosen (1992) grading standard model (Betts, 1997; Oettinger, 2002; Dubey and Geanakoplos, 2010). We then use this result, along with a list of other findings of the model consistent with grade-utility maximizing behavior, to guide our empirical design.[7]

To assess the effect of the shift to online learning on S/U uptake and the role of remote friendship, we define two time-periods and construct two dependent variables. The first time-period covers the days from the start of the Spring 2020 semester until just before the return home order and S/U deadline extension (March 10). The expected S/U deadline was March 17 at the time. The second time-period covers the days starting when virtual instructions began, to a revised S/U option deadline extended to the end of the semester but before grades were announced (May 12).[8] To look at the incidence of grade option choices, our first dependent variable is S/U uptake — an indicator for if students are taking a class S/U at the end of a period. To instead look at the incidence of preference switches between grading options within a period, our second dependent variable is S/U switch – an indicator for if students started with the graded option but switched to S/U within a period.

We use a generalized difference-in-difference estimation strategy with two-way (course-level and time) fixed effects. Callaway et al. (2021) provides the sufficient conditions in a continuous treatment environment for the difference-in-difference estimator to reflect the average treatment of the treated (ATT) for each treatment dosage. The key assumption required is parallel trends – the S/U uptake changes over time among students of the less impacted group should serve as a good proxy for the S/U uptake changes of the treated group had the treatment been withheld.

To test this assumption in our context, we leverage a longstanding Cornell residential housing policy which strongly encouraged all freshman students to live in university housing. Among students who enrolled as freshmen in Fall 2019, 99.6% lived in University housing.[9] These students must vacate university housing to return home after campus closure. By contrast, only

[7] These include predictions on a students' grade ability, course difficulty, their interactions, as well as cohort- and career-specific effects.

[8] As an unprecedented emergency measure, the S/U option deadline extension was meant to be an accommodation to students suddenly exposed the stress of a pandemic, allowing them time to consider adopting the S/U option after the return-home order took effect.

[9] This is according to the Fall 2019 Common Data Set collected by the Office of Institutional Research and Planning at Cornell University. University housing includes all Cornell owned-, operated- or affiliated housing.

39% of non-freshman undergraduates live in university housing. Our identification assumption requires that the mandatory return home treatment has no effect on the S/U uptake decisions among students for whom the treatment is withdrawn. Therefore to assess whether our findings are consistent with the parallel trend assumption, we not only assess whether the effects of the return home treatment are salient among freshmen students, we also verify whether the return home treatment made any difference to the S/U choices of upperclassmen, a majority of whom have off-campus housing options and thus need not return to their home addresses.

For freshmen, we find that a 1% increase in standardized distance to Ithaca is associated with a 0.9% (1.2%) increase in the likelihood to adopt (to switch to) the S/U option, and 1 standard deviation increase in internet coverage on average is associated with a 0.7% (0.7%) reduction in the likelihood of adopting (to switch to) the S/U option. These results double in female only subgroup analyses. S/U choices among the subsample of Non-STEM and Non-URM students are likewise more salient than STEM and URM students respectively.[10] The S/U switch regression results mirror this pattern. Using Shapley decomposition, we find that the return home treatment explained 7.4% of the R-square from the freshmen-only S/U choice regression, and 38.3% of the R-square from the freshmen-only S/U switch regression.

On the parallel trend assumption, we confirm that conditional on controls, non-freshman students, a majority of whom did not live in on-campus housing, behaved no differently than students with local permanent home addresses. We also looked at specifications separately for freshmen and first-semester sophomores in Spring 2020, as well as specifications that include course fixed effects. The null return home treatment effects for non-freshman remain robust in these alternative scenarios. In addition, we run placebo tests regressing before return home treatment S/U choices and switches on future return home treatment intensities and did not find non-COVID related spurious correlations to be an important concern.

To make sense of the effects of the return home treatment, we speculate that student exposure to the challenges of the virtual learning shock may be further differentiated depending on the availability of class-specific support by both instructors and remote peers. We account for the former with course fixed effects. For peer support, we extract measures of a student's friendship network in each enrolled course from the university administrative data set.

[10] We unpack these distinctive differences in Section 7.2 by examining the distribution of cumulative GPA's relative to course median by student subgroups.

Specifically, for each student-course observation, we count the number of students who are (i) alumni of the same high school, and (ii) members of the same Greek chapter. We also calculate, at the gender-course and ethnicity-course level respectively, the fraction of students who are (iii) of the same gender, and (iv) of the same ethnicity. While (i) and (ii) capture the student and class-specific count of individuals who are arguably likely to be known acquaintances, henceforth friends in a class, (iii) and (iv) are group attributes in a class that facilitate group learning and peer effects in a classroom environment based on previous studies (e.g., Hoxby, 2000; Sacerdote, 2014; Calvó-Armengol et al., 2009; Isphording and Zölitz, 2020; Getik and Meier, 2024). We use these metrics to assess whether friendship networks can compensate for the learning challenges of a virtual instruction shock.

Importantly, we find (i) having at least one friend in class on average decreases the incidence of S/U uptake and S/U switches among freshman students by 1.5% and 1.1% respectively, and (ii) in subsample analyses S/U uptake and S/U switches among students with at least one friend in the classroom based on common high school and / or common Greek chapter head counts are no longer responsive to distance from campus and internet access. To assess the mechanism driving these results, we argue using additional evidence (e.g., timing of S/U switches, grade outcomes among students who opted for the graded option, S/U uptake responsiveness to course difficulty) that remote friendship is an effective source of academic support during the remote instruction period, and physical distance in fact underscored the advantage of having a friend in class. We also rule out alternative mechanisms due to composition effects and correlations with other student characteristics.[11]

Complementary to these causal return home treatment effects, we also find additional, albeit non-causal, evidence about how S/U uptake decisions are driven by grade conscious preferences and other student and course characteristics. Consistent with the findings of the model, the gap between cumulative GPA of a student and the past median grade of a course – a proxy for a student's ability in a given class – has nonlinear (inverted U shaped) effect on S/U uptake. Students in the highest and the lowest ability quintiles are the least likely to use the S/U option. Students in difficult (with low past course median grades) or high-enrollment courses are also more likely

[11]We rule out alternative mechanisms that may drive spurious correlations (e.g. correlations with gender, urm status, stem-major choice, and course difficulty relative to a student's GPA) and show that the friendship effect is unlikely to be driven by composition. We also find that remote friendships help explain the effect of distance from campus on S/U uptake even after controlling for internet access. In particular, students with home addresses that are far away from Ithaca have less friends, but similar average levels of internet access.

to use the S/U option. These results suggest that S/U uptake decisions are largely in line with its original intent of the grade option policy – to allow students to take more challenging courses and to alleviate stress and anxiety when course loads are heavy.

We take from this evidence a number of lessons. Our findings show that even before the pandemic, students have leveraged the S/U option as a coping strategy depending on course difficulty, own-ability, and major, for example. Controlling for these factors, the unexpected COVID19 return home order proved significant enough for subgroups of students (freshman, predominantly female students, and non-STEM majors) to give up on the opportunity for graded work in favor of an S/U option – a large fraction of whom did so in the final weeks of the semester. However, having a friend in class, even when friends are physically separated from campus, mitigated against the learning challenges brought on by the return home order. In these respects, the COVID19 experience provided a unique opportunity to gauge the sources of learning challenges with online instruction during a pandemic, and deepened our understanding about the importance of peers in virtual classroom settings.

2 Literature and Contributions

Many of the grade-option choice controls used in this paper are motivated by a large literature on the determinants of academic performance. These include class size (e.g., Angrist and Lavy, 1999; Jepsen and Rivkin, 2009; Rivkin et al., 2005), gender (e.g., Conger and Long, 2010), ethnicity (e.g., Arcidiacono and Koedel, 2014) and peer effects (e.g., Calvó-Armengol et al., 2009; Agostinelli et al., 2020). Our goal is to confirm whether the set of factors with proven impact on academic performance is reflected in grade option choices – an indicator of perceived learning performance as assessed by the students themselves. In the literature, the effect of peer networks in the classroom as a source of performance-enhancing support in in-person settings is now well understood (e.g., Hoxby, 2000; Sacerdote, 2014; Calvó-Armengol et al., 2009). In this context, the innovations of this paper are two-fold: (i) to assess salience of remote friendship as a source of peer support in virtual instruction settings, and (ii) to introduce two headcount measures of in-class friendship – the number of classmates from same high school, and the number of classmates in the same Greek chapter. We show that having a friend in class, even after instruction goes virtual, offsets the effect of return home treatment, as well as the effect of other course-related triggers of S/U uptake, such as course difficulty.

This paper also contributes to the literature on the impact of online learning on academic performance in general. Studies have used randomized control design (e.g., Kofoed et al., 2021; Figlio et al., 2013), or large administrative data sets (e.g., Altindag et al., 2021), employing various fixed effects models (Hart et al., 2018), instrumental variable estimation (e.g., Bettinger et al., 2017; Xu and Jaggars, 2013), or propensity score matching (Xu and Jaggars, 2013). These studies generally find that distance learning has a negative effect on learning outcomes, with some exceptions (e.g., Bratti and Lippo, 2022). Our study complements these findings by using university administrative data and the quasi-experimental return home shock of the Spring 2020 semester to shed light on some of the underlying mechanisms driving learning challenges in an online environment, including internet access, and separation from peers.

This paper contributes to a growing literature on the role of COVID19 in higher education academic outcomes by providing a causal study of the determinants of student uptake of grade option choice accommodations as a result of the transition to virtual learning.[12] Studies have used a variety of approaches to capture the impact of the pandemic.[13] Among these, three studies are most closely related to our work in that they employ university administrative data to examine the impact of COVID19 on academic performance.[14] In particular, Rodríguez-Planas (2022) uses data from Queens College to shed light on the heterogeneous impact of COVID19 on grade performance by income groups and student ability. The flexible grading policy at Queens College in the Fall and Spring semesters of 2020 was different from the Cornell setting in that students did not know their letter grade at the point of choice at Cornell, whereas in Queens College students could change grading option to credit / no credit after they have seen their posted letter grades. The study finds that low-income students are more likely to exercise the flexible grading option. This served to offset the adverse GPA effect of the pandemic for students with relatively low pre-pandemic cumulative GPA, but not sufficiently so for low-income top-performing students.

[12] There are also a small number of studies that evaluate student performances during COVID19 in specifically economics classes. These have shown mixed results. See for example (Brown and Liedholm, 2002; Engelhardt et al., 2021; Orlov et al., 2021).

[13] Studies have also used survey data both within the United States and across countries to demonstrate the disruptive impact of COVID-19, in terms ranging from academic performance expectations (Aucejo et al., 2020; Barnum and Bryan, 2020) course completion, graduation plans, and retention rates (Rodriguez-Planas, 2022; Jaeger et al., 2021). These studies have also demonstrated labor market effects of COVID19, including job losses and earning reductions Rodriguez-Planas (2022), disproportionate labor market disruptions borne by female students, acceptance of jobs with negative characteristics for example (Jaeger et al., 2021). Kofoed et al. (2021) finds that face-to-face instruction dominates online instruction in a study based on random assignment of West Point cadets in Fall 2020.

[14] Also see De Paola et al. (2023) which present evidence of procrastination as a key barrier to learning in an online environment in an Italian University using administrative data.

In a related study, Ozsoy and Rodriguez-Planas (2023) finds that users of the flexible grading option at Queens College during the pandemic tend to have poorer academic outcomes (e.g. lower GPA, withdrawal from class, lower likelihood of graduation) in subsequent semesters. The study also provides a student-level and non-causal breakdown of the characteristics of ever-users of the flexible grading policy during the pandemic semesters (e.g. self-reported challenges due to COVID19 including challenges with learning via the internet, as well as age, past cumulative GPA, and ethnicity).

A third closely related study is based on a large administrative data set with over two million student-course-semester observations in a community college in Virginia Bird et al. (2022). The study uses within-instructor-by-course variation on whether students started their spring 2020 courses in person or online with student fixed effects to show the impact of COVID19 on course completion rate and grades. The study finds that online instruction during COVID19 is associated with a modest reduction in course completion rate, and no longer term impacts.

Our work differ from these important studies in a number of ways. First, we do not just rely on end-of-semester outcomes, but rather we use daily observations of the student record to see whether grade option choice behavior change within each student-course unit and if so and at what point during the semester for each student-course observation. Second, we do not group together all students as treated or not treated, but rather we compare the behavior of students most likely impacted by the return home treatment (i.e. freshmen students, those who live farther away, with poorer local internet coverage), with students with local addresses. Third, we look inside the student composition of each student-course observation to tease out the peer student network that a student may have access to in order to explore effective coping mechanisms available to students even in a virtual environment. Finally, we use grade option choice as a student-assessed measure of perceived grade performance, rather than (i) course grades as grade inflation in the Spring 2020 semester may have had differential incidence on individual students and student groups that will affect how we should interpret any findings, or (ii) course completion rates as course completion is uniformly high during the Spring 2020 semester at Cornell University, potentially as a result of the changes in grade option deadlines.

3 Policy Background

3.1 S/U Option

There are three types of courses at Cornell University: graded-only, S/U only, and student-optional. Students can only take graded-only courses for a letter grade and can only take S/U only courses with the S/U grading option. For student-optional courses, students have the freedom to either take them for graded or with the S/U option. Around 50% of courses at Cornell offer student the freedom to choose their grade option, meaning that these courses have the student-optional grading option. The S/U option provides an opportunity for students to explore unfamiliar subjects and to take courses of their interest without much pressure. Students taking courses with the S/U option receive a passing grade of S if they get a C- or higher and receive a failing grade of U if they get any grade below a C-. Students get the credit for the course if they receive a passing grade of S.

There are a few restrictions in terms of using the S/U option. The deadline to switch classes to S/U is usually the 7th week of the semester. Students adding courses after the deadline have to take the course for graded. There are some courses that cannot be taken with an S/U option, typically determined by the faculty instructor and the department offering the course, including for example prerequisite courses for graduate school and courses counted towards students' major and some minors. In addition, to fulfill the graduation requirement, students must earn a minimum of 80 credits from courses for which a grade is received.

3.2 Spring 2020: Return Home Order and Change in S/U Policy

With the outbreak of Covid-19 during the Spring 2020 semester, Cornell University issued a series of measures to de-densify the Ithaca campus and to minimize the chances of on-campus transmission. On March 10, 2020, students were notified that the instruction for the remaining semester would be virtual and would resume on April 6, 2020 after the spring break. Meanwhile, students are strongly encouraged to return to their permanent residences. In particular, all students were asked to leave campus no later than March 29, 2020, except those who received an exemption to stay in on-campus housing. In addition, the deadline to drop courses and change grade options was extended from March 17, 2020 to April 14, 2020 to allow students adequate time to make decisions.

On April 5, 2020, the day before virtual instruction resumed, students received another notice from university administration about the new grading policy for the semester. The deadline to drop courses or change the grade option to S/U was extended again to May 12, 2020, the last day of class. All courses, including previously graded-only courses, will now offer an S/U grading option. Courses taken as S/U and with a grade of S can be counted towards major and minor requirements, as well as college requirements for good standing and graduation. The policy was not without debate, and alternatives were considered before the April 5 announcement. Some objected to a universal S/U policy as course grades are seen as necessary for graduate school applications and to satisfy employment requirements. Others contend that expanding the S/U option can avoid marginalizing students with personal hardships, and in particular those with inadequate access to the internet and / or difficulty participating in class from distant time zones.[15]

4 A Conceptual Model of Grade Option Choice

We examine the patterns of S/U uptake decisions in a model featuring (i) grading standards that are correlated with student ability and (ii) student preferences that are a function of grade ranks (e.g., Becker and Rosen, 1992; Betts, 1997; Oettinger, 2002; Dubey and Geanakoplos, 2010).

Let $\mathcal{G} \in [g^-, g^+]$ denote the range of feasible course grade points —- higher being better. Suppose that student i's grade in course k ($g_{ik} \in \mathcal{G}$) relative to the median grade ($g_{med,k}$) is a function of the student's grade ability in the course ($\gamma_{ik} \in \mathcal{G}$). γ_{ik} reflects the student's innate ability, accounting for course-specific features such as course difficulty, class size, and peer support, for example:[16]

$$g_{ik} = g_{med,k} + f(\gamma_{ik} - g_{med,k}) - \lambda_{ik} + \epsilon \tag{1}$$

where the course grade mapping $f(\cdot)$ is defined on the range $[g^- - g_{med,k}, g^+ - g_{med,k}]$. We assume that the following properties of $f(\cdot)$ hold: (i) the median-ability student gets the median grade ($f(0) = 0$) on average, and (ii) students with higher abilities get higher grades ($f'(\cdot) \geq 0$). $f(\cdot)$ may be strictly convex or concave depending on whether grade ability exhibits increasing (decreasing) marginal returns if $f''(\cdot) > (\leq) 0$.

The return home order impacts students' course grade expectation through the shifter λ_{ik}. Intuitively, a student with a median grade ability may no longer expect a median grade if $\lambda_{ik} > 0$.

[15] See Kamis (2020) for a report on the Cornell Faculty Senate deliberations in April 2020 on the pros and cons of removing the graded option altogether and universalizing the S/U option. The proposal to make S/U mandatory was ultimately voted down.

[16] Course grades will also depend on effort and study time. We think of γ_{ik} as the optimized grade ability of a student accounting for effort cost.

Naturally, students may also have expectations about possible grade accommodations during a pandemic, thus offsetting the grade impact of learning challenges associated with online instruction. Since we will not be able to separately identify these two opposing forces in our empirical work, we think of λ_{ik} as the net effect (grade penalties due to online learning barriers net of grade inflation) of the return home order on grade expectations. In effect, if we find evidence supporting $\lambda_{ik} > 0$ and grade inflation was present, then the actual effect of learning barriers is arguably even higher. Finally, ϵ is a random error term with zero mean due for example to randomness in exam performance or grading error.

Let c_i denote student i's cumulative GPA prior to taking the course. Taking course k for a grade increases the student's cumulative GPA going forward, on average, if

$$c_i < g_{med,k} + f(\gamma_i - g_{med,k}) - \lambda_{ik}.$$

Beyond grade opportunism, student preference regarding the S/U option may also embody major-specific norms about the ability-signaling role of an S/U grade. Students may also exhibit different levels of grade risk tolerance. Thus, we assume that a student will prefer the S/U option if and only if

$$c_i \geq g_{med,k} + f(\gamma_i - g_{med,k}) - \lambda_{ik} + \eta_{ik} \tag{2}$$

where η_{ik} is an S/U preference shifter.

We relegate the proofs of the following model findings to the Appendix. In particular, the likelihood that a student chooses the S/U option, all else constant (i) increases when the return-home order decreases grade expectations, $\lambda_{ik} > 0$, (ii) decreases for students with higher grade abilities, γ_{ik}, and (iii) decreases when students take into account other S/U option deterrents encapsulated in η_{ik}, due, for example, to employment considerations or risk preferences.

In addition, the model generates a non-monotonic relationship between S/U option choice and a student's prior GPA c_i conditional on course difficulty. Specifically, if the grade performance mapping $f(\cdot)$ exhibits increasing marginal returns, students with intermediate levels of cumulative GPA conditional on course difficulty prefer the S/U option, while students with relatively higher and relatively lower levels of cumulative GPA prefer the graded option. In essence, high prior cumulative GPA students (relative to the course median) prefer to have their performance reflected in the course grade, while low cumulative GPA students stand to gain from getting a grade in a course with a high median.

5 Data

Our empirical analysis is based on three data sets. The first is Cornell University's administrative data set. The data is de-identified at the student-course level, and includes information on course enrollment, course grade option, course credit, and course grades. For Spring 2020, in particular, if a student chose to switch the grade option from graded to S/U, we have the exact date on which the student made the switch. In addition, we have de-identified individual level information in students' demographics, home residence, standardized test scores, cumulative GPA, major choice, athletics, and Greek life involvement.

We supplement this with three additional data sets, including the American Community Survey 2019, zip code level data on latitude and longitude for all zip codes in the United States, and measures of COVID exposure using smart phone (PlaceIQ) data (Couture et al., 2022), as well as from the Center of Disease and Control. From the American Community Survey 2019, we took zip code-level data on internet coverage and family income. With zip code level data on latitude and longitude, and calculate the distance between all zip codes in the United States and Ithaca, New York, where Cornell University is located.

5.1 Data Description

We construct seven categories of variables: return-home variables, student-course variables, student-specific variables, course-specific variables, career variables, group variables, and time indicator. In addition, our dependent variables are S/U uptake and S/U switch.

For our main dependent variables, "S/U uptake" is an indicator of whether students are taking courses S/U – 1 if the student is taking course S/U in the given time period and 0 otherwise. "S/U switch" is an indicator of whether students switched the grading option of the course to S/U in the given time period, conditional on not having done so before. It takes on value 1 if the student switches the course grade option to S/U in the given time period and 0 otherwise.

Our return home treatment variables are based on two dimensions of separation from campus resources. "Standardized Distance to Ithaca" measures the distance in miles from the zip code where the students' residences are located to zip code 14850 for the city of Ithaca (New York) where Cornell University is located. We then standardize by dividing by the standard error of distance. "Internet Coverage" measured at the zip code level reflects the percentage of households with internet coverage associated with the student's home address from the American Community

Survey 2019.

For course variables, we include "Past Course Median" as the median grade of a course the last time it was offered. "Past Course S/U Fraction" refers to the fraction of students taking courses S/U prior to Spring 2020.[17] We also include the number of "Students in Class" in addition to "Course level" to distinguish between introductory and more advanced courses based on whether the course number falls under one of four categories: 1000-2000, 2000-3000, 3000-4000, and 4000+. We construct an indicator for each category and use 1000-2000 the baseline group.

For student variables, we include "Female" as an indicator variable – 1 if the student is female and 0 otherwise. Ethnicity indicators are binary terms reflecting students' self-reported ethnic identities: "White" (base category), "Black", "Asian", "Hispanic", "Other", and "Multiple". "Credit Taking" counts the number of academic credits students took for Spring 2020. "Family Income" is the zip code-level mean family income corresponding to the students' residence addresses from the American Community Survey 2019. For interpretation, the variable is expressed as the logarithm of family income. Finally, "Greek Life" is an indicator for when the student is a member of a Greek chapter.

For student-course variables, we include "Cumulative GPA (Fall '19) " and "GPA-Median Grade Gap Quintiles" to assess a student's prior grade ability relative to the course median. For each student-course observation, we calculate the GPA-Median grade gap:

$$\text{GPA-Median Grade Gap} = \text{Cumulative GPA} - \text{Past Course Median}.$$

We then rank the gap and divide the observations into groups of students at the same class level (freshman, sophomore, junior, and senior). For each group, we sort observations into quintiles and construct indicators for each quintile. We use the lowest GPA-Median grade gap quintile as the base group. "Own Major" is an indicator variable that indicates that a course is of the student's own major department.

For career-related variables, we include "STEM Major", a binary indicator of whether a student was majoring in a STEM subject,[18] "Business-related Major" is an indicator for whether the

[17] For both past course median and past course S/U fraction, if courses were offered Spring 2019, we take fraction of students taking courses S/U from Spring 2019. If not, we take fraction of students taking courses S/U when they are most recently offered prior to Spring 2020.

[18] Majors included in this categor are: Animal Science, Atmospheric Sciences, Biological Engineering, Biological Sciences, Biomedical Engineering, Biometry & Statistics, Chemical Engineering, Chemistry, Civil Engineering, Computer Science, Dyson Business Engineers, Earth & Atmospheric Sciences, Economics, Electrical and Computer Engr,

student's major was from the College of Business, College of Industrial and Labor Relations, and Economics major.[19]

For peer group variables, we include "Number of Same High School Student" for each student-course observation as the count of the number of students that went to the same high school in the class. "Number of Same chapter Student" counts the number of students from the same Greek chapters in class for each student-course observation.[20] If we extend the pool of potential friends or sources of support to students of the same gender or ethnicity, the variable "Fraction of Same Gender Student" measures the fraction of students in class that are of the same gender as the student, while "Fraction of same Ethnicity Student" is the fraction of students in class that are of the same ethnicity as of the student.[21]

Finally, for time variables, in our setting the deadline for students to change grade options was extended twice, first on March 10 the deadline was moved to April 14, and subsequently again on April 5, the deadline was extended to May 12. We let $t = 0, 1, 2$ denote the time before March 10, between March 10 and April 5, and between April 5 and May 12. We include indicators for these 3 time periods.

The first period, before March 10, refers to days in the semester before the return home order was announced.[22] The second period, between March 10 and April 5, includes the days after the return home order was announced but before virtual instruction began.[23] The third period, between April 5 and May 12, refers to the days after virtual instruction began but before students have to petition to change the grade option for courses. During this period, students can change the grade option for graded-only courses and student-optional courses. In addition, the S/U deadline extension to May 12 is known throughout this period.

Engineering Physics, Entomology, Environmental Engineering, Food Science, Information Science, Information Science Systems & Technology, Materials Science and Engineering, Mathematics, Mechanical Engineering, Nutritional Sciences, Nutrition and Health, Operation Research & Engineering, Physics, Plant Sciences, Psychology, Science & Technology Studies, Science of Earth Systems, Science of Natural & Environmental Systems, Soil Science, and Statistical Science.

[19]These include: Applied Economics and Management, Policy Analysis and Management, Hotel Administration, Industrial and Labor Relations, and Economics.

[20]We have "Number of Same sport Athlete" counts for the number of students on the same sports team but this information is only available for sophomores, juniors and seniors.

[21]These are normalized by student enrollment in fractions to get at a support per student measure, for unlike the number of same high school or same Greek chapter students, we do not know the precise number of friends of the same gender or ethnicity for each student.

[22]Students did not know that they will be asked to return home at this time. They also did not know that there will be a change in the S/U deadline at this time. The expected last day to change the grade option was March 17 and only student-optional courses can be taken S/U.

[23]Students expected to return home and start virtual instruction on April 5. The expected last day to change the grade option was April 14 during this time, and only student-optional courses can be taken S/U at this time.

5.2 Summary Statistics

Table 1 and Table A1 provide an overview of the courses offered during Spring 2020, and the characteristics of students who chose to take courses S/U. As shown in Table 1, 1,214 out of a total of 2,328 courses offered were student-optional, 783 are graded only, and 331 were S/U only. This suggests that students had the option to change the grade option to S/U for 52.15% courses (student-optional only) before April 5 and 85.78% courses (student-optional and previously graded only) after April 5. Furthermore, for student-optional courses, the mean fraction of students taking courses S/U increased from 13.3% to 22.5% after the return home order, representing an increase of over 40%.

Table A1 provides a student-level look at S/U choices in Spring 2020. Of the 12,564 students enrolled during Spring 2020, 9,002 took at least one class S/U. This suggests that S/U is popular among students, and 71.65% of students used the option. On average, students took 33.2% (3.4% from S/U only courses, 12.4% from Grade only courses, and 17.4% from Student Optional Courses) of their credits S/U. For students who took at least one course S/U, they on average took 46.3% (4.8% from S/U only courses, 17.2% from Grade only courses, and 24.3% from Student Optional Courses) of their credits S/U. Across class levels, freshmen and seniors used the S/U option more.

To compare S/U uptake frequencies in the Spring 2019 semester before the pandemic, and in Spring 2020, Figure 1 shows the fraction of student-course level S/U uptake for three course samples: all courses, student-optional courses, S/U only courses, and graded-only courses in the two semesters. While 13.5% of all student-course level observations were S/U during Spring 2019, 27.5% of all student-course level observations were S/U during Spring 2020. The fraction of student-course level observations that are S/U almost doubled from Spring 2019 to Spring 2020, suggesting that students' S/U behavior changed in Spring 2020. Furthermore, from spring 2019 to spring 2020, the fraction of student-course-level observations that are S/U for student-optional courses increased from 6.8% to 21.2%, and for graded-only courses the uptake of S/U increased from 0% to 10.5%. During Spring 2020, students used the S/U option more across both student-optional and graded-only courses.

Using daily observations on S/U uptake, Figure 2 shows that a majority of the grade option changes took place between April 5 and May 12 and close to May 12, the last day to change grade option without penalty. This provides some suggestive evidence that the change in students' S/U uptake behavior occurred between April 5 and May 12, after the return home period.

To examine the relationship between S/U uptake and distance from campus as well as S/U updtake and internet access, Figure A1 provides a pair of binscatter plots showing the propensity of students to switch courses to S/U for all courses by distance from home address from Ithaca and by coverage of the internet at home zip code level. We see that S/U switches appeared to be more frequent in far away locations. Likewise, S/U switches were also more common in areas with relatively poor internet access. We note that there is a clustering of observations in geographically nearby locations with diverse S/U switch behaviors, but not based on internet access. This reflects a high concentration of students who are from geographically proximate home addresses. We shall return to this point later on in the analysis.

5.3 Sample Construction

We impose several restrictions on our main sample. In particular, we focus on domestic students with home addresses within the continental US. Our quasi-experimental setting relies on the assumption that students return to their permanent residential address after the return home order was announced. However, students with international addresses can face different levels of travel restrictions between countries and regions, limited supply of expensive flight tickets, and uncertainty regarding future return to campus. Instead of returning home, such students may choose to stay in the United States with relatives or friends. Therefore, we choose to restrict our attention to domestic students who are more likely to return to their residential address.[24] [25]

In addition, we focus on student-optional courses, namely courses with pre-existing S/U options for two reasons. First, for previously graded-only courses, the dynamics of S/U uptake conflates the S/U policy relaxation for these courses and the return home mandate. Furthermore, in courses without a prior S/U option, students might have been unsure about the performance cutoff required for an S grade.

We also focus on the comparison between before March 10 and between April 5 and May 12. We do so because between March 10 and April 5, instruction was suspended, and students can choose to return to their permanent home address any time before April 5. Therefore, we focus

[24]We also remove the handful of students from Hawaii and Guam for similar reasons for our main analyses. Including these observations does not change our qualitative results and these tables are available in the Appendix.

[25]To the extent that home address may not perfectly capture the students actual distance from campus for some students, the return home coefficients will be biased towards zero, implying for example that a positive estimated coefficient should have been more positive had the error been corrected. Thus, a positive estimated coefficient in this case will imply an even more positive effect accounting for the possibility of measurement error.

on the time periods when we are certain that the students have begun to experience the change in study environment if they have indeed returned home.

With these restrictions, our regression sample contains $33,543$ student-course-level observations from $11,977$ students. As shown in Table A2, $11,977$ (out of a total of $12,564$) students took at least one student-optional course, meaning that our sample contains roughly 95.3% of the total student population, and thus the characteristics of the regression sample is very similar to the overall sample. After expanding it into a panel structure with two time periods, we have $67,086$ student-course-level observations.

6 Empirical Strategy

Our empirical strategy is a generalized difference-in-difference design with two-way fixed effects, to include a course-level (j) and a time (t) fixed effect. Callaway et al. (2021) provides the sufficient conditions in a continuous treatment environment for the difference-in-difference estimator to reflect the average treatment of the treated (ATT) for each treatment dosage. The key assumption required is parallel trends – the S/U uptake changes over time among students of the less impacted group should serve as a good proxy for the S/U uptake changes of the treated group had the treatment been withheld.[26] In other words for all treatment intensities $D = d$, the expected outcome (Y) change across the two periods t and $t-1$ of the untreated group is equal to expected outcome change for the treatment group had the treatment been set to zero ($D = 0$):

$$E[Y_t(0) - Y_{t-1}(0)|D = d] = E[Y_t(0) - Y_{t-1}(0)|D = 0].$$

Callaway et al. (2021) shows that under these conditions, the ATT for each treatment dosage is identified.[27]

To explicitly test this assumption, we need to be able to assess the behavior of students /

[26]The other sufficient conditions include (i) iid panel data, (ii) some units are not treated in any period, (iii) units cannot change their pre-treatment outcome after treatment.

[27]For an even stronger assumption to additionally identify the average treatment effect, Callaway et al. (2021) defines strong parallel trend – for all treatment intensities, d:

$$E[Y_t(d) - Y_{t-1}(0)] = E[Y_t(d) - Y_{t-1}(0)|D = d],$$

requiring that averaging across all individuals, the expected change in outcome across two periods due to a given treatment intensity is the same across all individuals regardless of their assigned treatment intensities. This is a strong assumption that may not hold, and in any case is a challenge to verify in our context. The assumption asserts that an individual's prior lived experience with one's assigned treatment (namely virtual learning depending on home distance from campus and internet access) does not matter, and thus putting any other person at the same distance from campus would yield identical grade option choices.

student groups for whom the return home treatment was withheld. To this end, we separately assess the S/U uptake decisions of freshmen – for whom it is mandatory to live in university-provided dormitories prior to the return home order, and those of upper class men, a large fraction of whom live in off-campus housing and thus can choose to remain untreated by staying in off-campus housing.

For a student i taking course c at time t, we let SU_{ict} be a vector containing student i's S/U uptake and S/U switch decision for course c at time t. For S/U uptake, SU_{ict} takes the value 1 if student i is taking course c S/U at time t and 0 otherwise. For S/U switch, SU_{ict} takes the value 1 if student i switched the grading option of course c to S/U at time t and 0 otherwise, conditional on not having done so before t. We define seven categories of variables that affect students' S/U uptake and switch decisions: return home treatment, student-course-level controls, student-specific controls, course-specific controls, career-related controls, group-level controls, and time. With these seven categories of variables, our main empirical specification is as follows.

$$\mathrm{SU}_{ict} = \alpha + \sum_k \beta_k x_{ikt} + \sum_l \delta_l y_{icl} + \sum_n \phi_n w_{in} + \sum_m \gamma_m z_{cm} + \varrho_i + \rho_t + \epsilon_{ict}$$

where x_{ikt} are student-specific time-varying return home treatment variables including the distance between their residence and Ithaca and internet coverage at their residence zip code. y_{icl} are time-invariant student-course level controls including students' cumulative GPA before Spring 2020, courses' past median grades, the gap between a student's cumulative GPA before Spring 2020 and the past median grade of the course, and if the course is of students' own major. w_{in} are student-specific controls including gender, ethnicity, and the count of academic credit load. z_{cm} are course-specific characteristics including the number of students in class and past students' S/U uptake. ϱ_i is a vector capturing career-related controls and group level controls for student i. This includes STEM major, business-related major, involvement in Greek life, and network controls indicating the (proxy) number of friends of a student, or the count of individuals of the same identity per student in class. ρ_t denotes time fixed effect for $t = 0, 2$, and ϵ_{ict} denotes a random error term.

The specification is estimated with a linear probability model by class-level. Since students were only allowed to switch from graded to S/U and not vice versa, during the grade option extension (treatment) period, the S/U switch regressions are estimated conditional on not having switched to S/U already before the treatment period. We adopt a random-effects generalized least-squares specification to account for heteroskedasticity. Standard errors are clustered at the student-course level.

Our main coefficients of interest are the β_k's, which show the return home effect on the propensity of S/U uptake and S/U switch. We conduct subgroup analyses to assess whether the salience of the return home treatment are subgroup-specific, depending in particular on access to remote friends. According to the model, a return home treatment effect that negatively affects the grade expectations of a student will raise the likelihood of the S/U option and S/U switch. While our results for S/U uptake capture average treatment effect of the return home treatment on students' S/U decision using end of period observations, our results for S/U switch capture changes in S/U preferences within a period depending on exposure to separation from campus. In addition, we are also interested in estimated results on δ_l, ϕ_n, γ_m, and ϱ_j. Though not causal, these results also provide important insights on how different types of students and circumstances are associated with the use of the S/U option.

7 Pooled Baseline Results by Class-levels

S/U Choice, S/U Switch, and Parallel Trends

As shown in Table 2, a 1% increase in standardized distance to Ithaca increases S/U uptake of freshmen by 0.9%. A 1% increase in internet coverage decreases S/U uptake of freshmen by 0.114%. With a baseline mean internet coverage of 89.3%, a one standard deviation increase of 6.75% in internet coverage increases S/U uptake among freshmen students by 0.77%.

Note that the effects of standardized distance to Ithaca and internet coverage on students' S/U uptake are only salient among freshmen students. In the 2019-20 academic year, 99.6% of students enrolled as freshmen in Fall 2019 lived in University housing.[28] Meanwhile only 39% of non-freshman undergraduates live in university housing and as such a majority of the these students could withhold the return home treatment by just remaining in their off-campus housing. Parallel trend requires that for individuals who opt out of returning home, their grade-option choices should be no different than those individuals in the control group – students whose home address is in Cornell's (Tompkins) county, conditional on controls. Indeed, we find that the estimated return home treatment effect of students in non-freshman classes relative to students with a Tompkins county address, where Cornell is location, are statistically no different than zero.

[28]This is according to the Fall 2019 Common Data Set collected by the Office of Institutional Research and Planning at Cornell University. University housing includes all Cornell owned-, operated- or affiliated housing.

In Appendix Tables A3 and and A4, we present return-home estimates within courses across class levels by introducing course fixed effects. We also examine findings from specifications using only data from students who were second-semester freshmen during Spring 2020 (Table A5). These students were just one semester more senior than freshmen students in Spring 2020 but were not required to live on campus due to their sophomore status. In all of these alternative specifications, we do not detect a salient return home effect on non-freshman students. We also performed placebo tests regressing S/U choices and switches before the return home order on future return home treatment intensities and found no spurious correlations (Table A6). These findings address concerns that we may be erroneously attributing student ability characteristics associated with distance and internet access as a return home effect.

Another way to address the concern that return home treatment intensities may be correlated with other freshmen student characteristics that can then influence S/U choice is to use the S/U switch variable. S/U switch looks at the role of the return home treatment at the margin, by gauging whether a student switched the grading option of the course to S/U within a given time period. If returning home affects the S/U uptake decision because it is correlated with student characteristics rather than the actual need to leave campus because of the return-home order, we would expect that the dependence would only show up before the move. Thus, actually returning home should not introduce an additional effect on student-course-level S/U switches.

However, as shown in Table 3, the effect of standardized distance to Ithaca on the students' S/U switches is once again salient and only among freshmen. Specifically, a 1% increase in standardized distance to Ithaca increases the likelihood of S/U switches by freshmen by 1.2%. Meanwhile, a 1% increase in internet coverage on average leads freshmen 0.1% less likely to take courses S/U. We will fine-tune these results further in subgroup analyses in the sequel, where the salience of the return home treatment effects on both S/U choices and S/U switches is shown to differ greatly by student groups.

These findings echo the concerns of university administration and faculty about multiple possible scenarios when students return home (Kamis, 2020). Limited internet coverage makes access to virtual lectures, learning resources, and course materials difficult. We show that students confronting weak internet access were indeed more likely to forgo receiving a grade.[29] Furthermore, distance and time differences can limit access to synchronous (albeit remote) delivery of lecture

[29]Note that we control for log family income (zip code level) in all regressions and as such these zip code level internet coverage effects are distinct from learning barriers associated with a lack of family resources in general.

materials and attendance in online office hours. Students in far away locations may also find it difficult to keep in touch with familiar study partners. In Section 8, we will further unpack these possible interpretations of the mechanisms that may have driven these return home effects.

Additional Return-Home Controls and Specifications

We also explored alternative controls to capture heterogeneous exposure to return-home effects. For distance, we considered measuring distance from campus as the number of time zones away from campus (Table A9). These are in line with our earlier discussion.

We also considered explicitly controlling for the severity of COVID exposure as an additional confounding factor. Since COVID infection is arguably more likely in locations where people come in contact with each other directly or indirectly as people travel or commute from place to place, we adopt the location exposure index of (Couture et al., 2022), LEX, and COVID infection data from the U.S. Center for Disease Control and Prevention (CDC) to construct a COVID exposure index to capture the fact that COVID infections has spatial spillovers, "LEX COVID exposure".[30] We find that COVID-exposure has the right sign but is not statistically significant contributor to S/U uptake in baseline regressions.

Other Controls: Course-Level

Henceforth, we report S/U option and S/U switch regression results related to course-, student-course-, student-, career, and peer group controls. As noted before, these results are non-causal. We nonetheless find these effects to be informative about whether students appear to use the S/U option as intended, particularly since previous empirical work in this area is rare.

As a pedagogical tool, the S/U grade option enables students to take more challenging courses without a grade penalty, and allows students to adjust grade-related stress levels and anxiety on their own (Mclaughlin et al., 1972; Marshall, 1973; Bain et al., 1973). From Table 2, students taking courses with higher past median grade, a proxy inversely related to course difficulty, are less

[30]The index "LEX", an NxN matrix constructed using location tracking data from smartphone pings. For each cell of the matrix, "LEX_{ijt}" measures the fraction of smart phones that pinged in each state j in the two weeks prior to date t, among the pool of smart phones that pinged in a given state i on date t. We think of LEX_{ijt} as a measure of people's mobility between locations i and j. Using daily-level "LEX" from Couture et al. (2022) and COVID infection case data from the CDC, we construct mobility weighted COVID exposure index of state i as the weighted average exposure of state i to new COVID infections for every 10,000 people in connected states j, COVID_{jt}. The weights are given by the mobility between the two locations as measured by LEX_{ijt} for every state i and $t = 0, 1, 2$:

$$\text{LEX COVID exposure}_{it} = \sum_j \text{LEX}_{ijt} \times \text{COVID}_{jt}.$$

We have also run other specifications without spatial spillovers and these results (available upon request) without spatial spillovers are not statistically significant.

significantly likely to take courses S/U across all class levels, with larger effects in magnitudes for freshmen, sophomores and juniors. The patterns for S/U switches are the same as shown in Table 3. Unlike return-home effects that tend to be sharply different across class levels, these course-level correlates of S/U uptake have largely similar effects regardless of class levels.

We also see that students across class levels are generally less likely to take courses S/U within their major. In other words, students are more likely to take courses outside of their major with the S/U option. This is consistent with a desire to explore new areas of interest, where the need to signal high achievement through a course grade is arguably not as intense.

Student-Course Controls

Quite apart from its pedagogical roots, the S/U option also allows students to improve their cumulative GPA. Our theory shows that the relationship between a students grade-ability in a course may be related to S/U uptake in non-linear ways depending on the nature of the course grade and student ability mapping.

Controlling for the prior cumulative GPA of the student and the past median grade of the course, we find that the effect of the GPA-Median grade gap is indeed non-linear. In Table 2, the lowest GPA-median grade gap quintile is used as the reference group. Students with intermediate cumulative GPA levels relative to the past median grade are more likely to adopt the S/U option, while students with either very high or very low GPA gap from past course median are relatively more likely to choose the graded option. In our model featuring grade opportunistic students (i.e. they hold grade rank dependent utilities), these findings are what we would expect when the relationship between course grade and student grade-abilities exhibits increasing marginal returns. In other words, students with higher cumulative GPA and higher grade-ability stand a high chance to do extremely well in the course, and will therefore opt out of S/U. A student with very low cumulative GPA relative to the course median may view a course as an easy class and thus will also prefer a grade.[31] Overall, we see from Table 2 that by the time students are about to graduate, these grade opportunistic effects along the GPA-median grade gap distribution have waned.

Student and Career Controls

From the S/U choice results in Table 2 and Table 3 we see that S/U choices and S/U switches

[31] There are alternative mechanisms that we do not rule out. For example, a student looking for a new major, say, may be starting off with a lower cumulative GPA, but will nonetheless be highly incentivized to take a class for credit to develop competency or to gain entry to a new major.

reflect students navigating the norms and requirements of their chosen major and career. For example, students in STEM majors are less likely to use the S/U option. This may be because course grades can be a signal of technical competencies. These effects tend to be most salient in their freshmen year, when major requirements may be most rigid, and senior year just before graduation and employment in both S/U choice and S/U switch regressions.

Female students are less likely to select an S/U grade as shown in both S/U uptake and S/U switch regressions. Being female is associated with a 2.9 % (freshmen) to 7.8% (senior) lower likelihood of S/U choice.[32] Across ethnicity groupings, we do not see a consistent pattern in S/U choice or S/U switch preferences across class levels.

Students carrying heavy credit loads are in fact less likely to adopt the S/U option, suggesting that a high credit load is another way to locate students with the ability and curiosity to take more classes. These students are arguably less likely to require an S/U accommodation.[33]

Group Controls

The effects of peer group support are nuanced. Of the four peer group controls included (fraction of same gender and same ethnicity students, number of high school and Greek chapter friends), there is not a single magic bullet that affected S/U uptake in all four class levels.[34] However, in general, each one of the statistically significant effects point consistently to peer support *decreasing* the S/U choice probability. We will return to these points in Section 8.

7.1 Shapley Decomposition

To assign relative importance to factors that affect S/U uptake and S/U switch decisions, we decompose R^2 and construct group-level Shapley values for return home treatment variables, student-course-level controls, student-specific controls, course-specific controls, career-related controls, group-level controls, and the time indicator. As shown in Table 4 for the S/U Choice

[32] One may also speculate that students differ in terms of their risk preferences. From this perspective, one would interpret our S/U choice findings in Table 2 as reflecting that female students are less risk averse than males, and likewise STEM students are less risk averse than non-STEM students.

[33] It is worth noting again that these are non-causal effects. Thus the correlations could point to students seeking grade pressure relief when workload is high, or that students can take on more credits when they can exercise the S/U option.

[34] These ambiguities may be arising potentially because of two opposing effects that are not easily disengtangled: students may gravitate towards courses where there are more friends even though the courses are not required and an S/U grade does not affect a student's grade-based performance. Meanwhile having more friends may also mean more peer support available in a classroom, which in turn reduces the need for an S/U grade. That said, such correlations may also be less intense for freshman students, as major requirements are more rigid early on and do not facilitate self-selection.

baseline regression, student-course level controls explain the largest fraction (39.17%) of R^2 followed by career- (19.51%), and student controls (14.22%). However, for our baseline S/U switch regression in Table 5, return-home variables explain the largest share of R^2 (38.37%), followed by the time indicator (35.73%) and student-course (17.15%) controls. This difference suggests that while group variables and course variables explain significant proportions of variation in students' initial S/U choice, the return home treatment explains a significant proportion of students' decision to opt into the S/U choice through the rest of the semester.

7.2 Heterogeneity

In Tables 6 and 7,[35] we perform heterogeneity analyses by gender, underrepresented minorities (URM), and STEM status to investigate whether the return home mandate may have had differential impacts on S/U choices and S/U switch decisions depending on student and career characteristics. As shown, the return home effects are most salient among female students, as well as students who are non-URM, and non-STEM. In each of these subgroups, the effect of the return home treatment is greater than the baseline estimates. In particular, a 1% increase in standardized distance to Ithaca increases freshmen female (non-URM, non-STEM) uptake of the S/U option by 2.0% $(1.0\%, 1.4\%)$. Meanwhile, a 1% increase in internet coverage decreases freshmen S/U uptake by 0.217% $(0.162\%, 0.145\%)$.

One way to think about these heterogeneous responses would be that different groups of students may have different preconceived notions or subjective preferences and interpretations about the net value-added of an S/U grade on their transcripts. While we cannot definitively confirm or rule out this purely group identity-specific possibility, we also look for other clues. From Tables 2 and 3, individuals who are least likely to switch to an S/U option are students in the highest GPA median grade quintile. A possible link between student types and return home effects on S/U uptake may simply be that the share of students most "at risk" of shifting in favor of S/U, because of their perceived ability to improve their GPA in the course, differs by student types. Figure 3 provides some visual evidence. We plot the GPA-median grade gap distribution by gender, URM status, and STEM designation, we find indeed that female as well as non-URM students have more left-skewed distributions. The larger concentration of students with cumulative GPA's just slightly higher than the median grade of the course may partly explain the salience of the return

[35]Tables A7 and A8 show the corresponding tables with course fixed effects. These show that even with the inclusion of course fixed effects, the return home treatment affect S/U uptake and S/U switches among female, non-URM as well as non-STEM students.

home effect on the S/U choices of these students during the pandemic.

For STEM students, we plot the same GPA-median grade gap distribution in Figure 3. Apparently, there is no discernible grade distribution skewness difference between STEM and non-STEM students. But in the case of Cornell, STEM students were more vocal about the need to keep the graded option in a pandemic because grades are needed as signals of technical competencies in employment and graduate school applications (Kamis, 2020). This career-specific S/U stigma is similar to the parameter η_{ik} in our model, which serves to negate the benefits of an S/U grade even in a pandemic.

8 What Drive the Salience of Remote Friendship?

It is by now well understood that online instruction poses significant learning challenges. Prior studies have relied on randomized control trial designs (e.g., Kofoed et al., 2021; Figlio et al., 2013), or large administrative data sets (e.g., Altindag et al., 2021), employing various fixed effects models (Hart et al., 2018), instrumental variable estimation (e.g., Bettinger et al., 2017; Xu and Jaggars, 2013), or propensity score matching (Xu and Jaggars, 2013) to make the point.

In this paper we make use of the unanticipated COVID19 return home orders and detailed personal friendship data inferred from administrative records to examine whether having a friend in the remote classroom can offset, at least partially, the challenges associated with online instruction. To begin, we create a binary variable, "Friends", to take on a value of 1 if a student has a least one high school or Greek life friend in the same class, and zero otherwise. To capture remote friendship, we then created the variable "Friends" $\times$ "Post Return Home" where "Post Return Home" is a binary variable equal to one for $t = 2$ and zero for $t = 0$. We use the "Friends" variable to replace the number of same high school and the number of same Greek chapter friends to get a sense of the discrete change in S/U preference between students with and without friends. In Table 8, we show the effect of S/U uptake and S/U switch regressions upon including the interaction friendship term "Friends" $\times$ "Post Return Home" and course fixed effects. We show results based on the full freshman sample, as well as subgroups by gender, URM, and STEM designation. We find that having a friend in class significantly decreases the likelihood of S/U uptake (between 1.5% and 2.1%) and S/U switch (between 1.1% to 1.5%) after the return home order depending on the subgroup. This suggests that students with a remote friend are less likely to resort to the S/U option after the return home order.

To go beyond average effects, we next examine the return-home effect on the subsample of student-course observations in which students have at least one friend in class. As shown in Table 9 and Table 10, both distance from campus and internet access are no longer statistically significant contributors to S/U uptake and S/U switches among students with at least one friend in class. This contrasts sharply with the without-friend subsample, where student-course and student-level controls, such as the GAP-median grade gap proxy for student ability, continue to play a role in driving S/U preference.

There are two possible mechanisms here. First, remote friends can serve as a source of virtual academic support during the pandemic, and as such physical distance alone is not enough to undo the benefits of having a friend in class. Having a familiar friend in class can be helpful when time zone differences and internet connections affect class and office hours attendance. Friends, even at a distance, can also serve as study partners, or as a source of emotional support while sheltering in place.

There are several observations we can make that are consistent with this mechanism. Starting from the motivations that prompted S/U uptakes and S/U switches, recall from Figure 2 that among students who switched to the S/U option in Spring 2020, a majority of these students waited until the last days before the deadline in May to make their choices. This provides suggestive evidence that academic performance is the predominant consideration in S/U uptake preferences, as students appeared as though they would really have preferred the graded option, but switched at the last possible moment presumably to preserve their GPA after having seen the results of their graded work up until that point.

Second, using the past median grade of a course as an indicator inversely related to course difficulty, Table A9 shows that within the subsample of students who have at least one friend in class, the past median grade of a course no longer triggers S/U uptake or S/U switches. In contrast, for students without a friend in class, the harder the class (the lower the past median grade), the more likely they will choose or switch grade option to an SU. This suggests that remote friendship appears to have the effect of offsetting the challenges of taking a difficult course in an online environment.

Third, if remote friendship really provides academic support, one would expect the effects to be present for students who opted for the graded option as well.[36] Furthermore, one might also

[36]We regress end of Spring 2020 semester course grade with the same list of controls used in the S/U regressions but

expect that friendship can help students navigate difficult courses better. From Table 11, these speculations are supported. The results there show OLS estimates of the determinants of Spring 2020 grades. These regressions use the full set of controls in our S/U regressions at $t = 2$, includes an additional interaction effect of friendship and the past median grade of a course. Course fixed effects are included to reveal within-class effects, and standard errors are clustered at the student-course level. The first two columns show results based on all student-course observations across class-levels. Freshman only results are shown in the next two columns. We find that remote friendship is a positive and statistically significant contributor to course grades in the Spring 2020 semester. Furthermore, the interaction effect is negative, thus providing suggestive evidence that having a remote friend in class enables a student to overcome the challenges of a difficult course. These findings confirm the message of a longstanding literature about the importance of friendship in class, and adds additional nuance by showing the salience of remote friendship in academically challenging courses.

Alternatively, as a second potential mechanism unrelated to friendship as a source of peer academic support, having a remote friend may just be a marker related to other confounding factors that govern S/U uptake sensitivity to return home effects. In Table 12, we look for these possible correlates of friendship links in class. The results are illuminating. First, we find that the subsample of freshmen students in courses with at least one friend in class has (i) more (3% points) female students, (ii) fewer (11% points) URM students and (iii) slightly fewer (less than 1%) STEM students. But notably, we have already seen in Table 6 and 7 that female, non-URM, and non-STEM students are *more* responsive to the effects of distance and internet access. Thus, if anything, these composition effect should render having a friend in class more sensitive to the effects of distance an internet on S/U uptake and S/U switches. However, Table 9 and Table 10 show just the opposite, suggesting that the effects of friendship on how students deal with the challenges of virtual instruction is unlikely due to these composition effects alone.

Table 12 also shows that the GPA median grade gap is slightly higher among freshmen students with at least one friend in class. This is fully consistent with the composition of students with friends being more likely to be female, and less likely to be URM as shown in Figure 3. Figure A2 compares histograms of GPA median grade gap distributions for students with and without a (high school, Greek chapter, or either) friend in class. In each case, the GPA median

only at $t = 2$ with course fixed effects and clustered standard errors at the student-course level.

grade gap distribution is more left skewed for students with friends. Thus, just like the female only, or the non-URM subsamples, the relatively higher GPA median grade gap suggests that students with friends confronting the challenges of virtual instruction are arguably more likely to favor the SU-option after the return home order to preserve their cumulative GPA. But once again contrary to what this composition effect might imply, we see that friendship in fact offsets the impact of distance learning on S/U-uptake (Table 9 and Table 10).

8.1 Understanding Distance – a Friendship Perspective

What is it about being physically far from campus that would explain a higher propensity for S/U uptake and S/U switches? This is puzzling, particularly since course materials, including recorded lecture videos, were made available both synchronously and asynchronously precisely to accommodate students living in different timezones during the Spring 2020 virtual instruction period.

We find that taking remote friendship relationships seriously enables us to better appreciate the role of distance on S/U choices. We take a cue from the spatial clustering of students by distance from campus in Figure A1, and speculate that distance from campus may be associated with the level of available peer support in a class. To wit, students applying to colleges may systematically favor universities in nearby locations due for example to familiarity and cost of moving. Students from home addresses close to campus, therefore, will in turn be relatively more likely to encounter a known face in class from their high schools. In Table 12, we indeed see that students with friends live closer to the Ithaca campus (on average by 216 miles) than the no-friends counterpart.[37]

Thus, distance from campus may capture both learning difficulties due to timezone differences and a decline in the number of friends a freshman student can expect to know well in a given class. To verify this possibility, we include another specification in which we look at the impact of timezone difference on S/U choice and S/U switches for sub-samples of students with and without at least one (same high school or same Greek chapter) friend in a class. We find that a greater timezone difference continues to have an impact on S/U uptake (Table A9). However, the effect is only weakly statistically significant for S/U choice, and insignificant for S/U switch.

[37]Figure A3 provides binscatter plots of the relationship between the number of other students from the same high school (Greek Chapter, or Either) and the distance of home address from campus in miles for each student-course observation. The graph controls for course-fixed effects to reveal within-course relationships between the number of high school friends in class and the distance of home address from campus.

These findings provides suggestive evidence that the role of distance is to some extent driven by its direct association with the access to remote friendship in a classroom.

8.2 Understanding Internet Access

Contrary to the case of distance from campus, we see in Table 12 that the levels of internet access are, in fact, similar between freshman students with or without friends in class. Yet poor internet access appears to only increase S/U uptake and S/U switches among students without friends as shown in (Tables 9 and 10). This evidence points to what university administration may have already anticipated: that differential Internet access can pose a challenge to students studying full-time in virtual environments (Kamis, 2020). An important lesson from our analysis in this context is that the burden of inadequate internet access can be offset if students are personally connected to other peers within the classroom. This kind of personal contact, although remote, is important, as revealed in the perception of course performance by students through their S/U choices (Table 9).

9 Conclusions

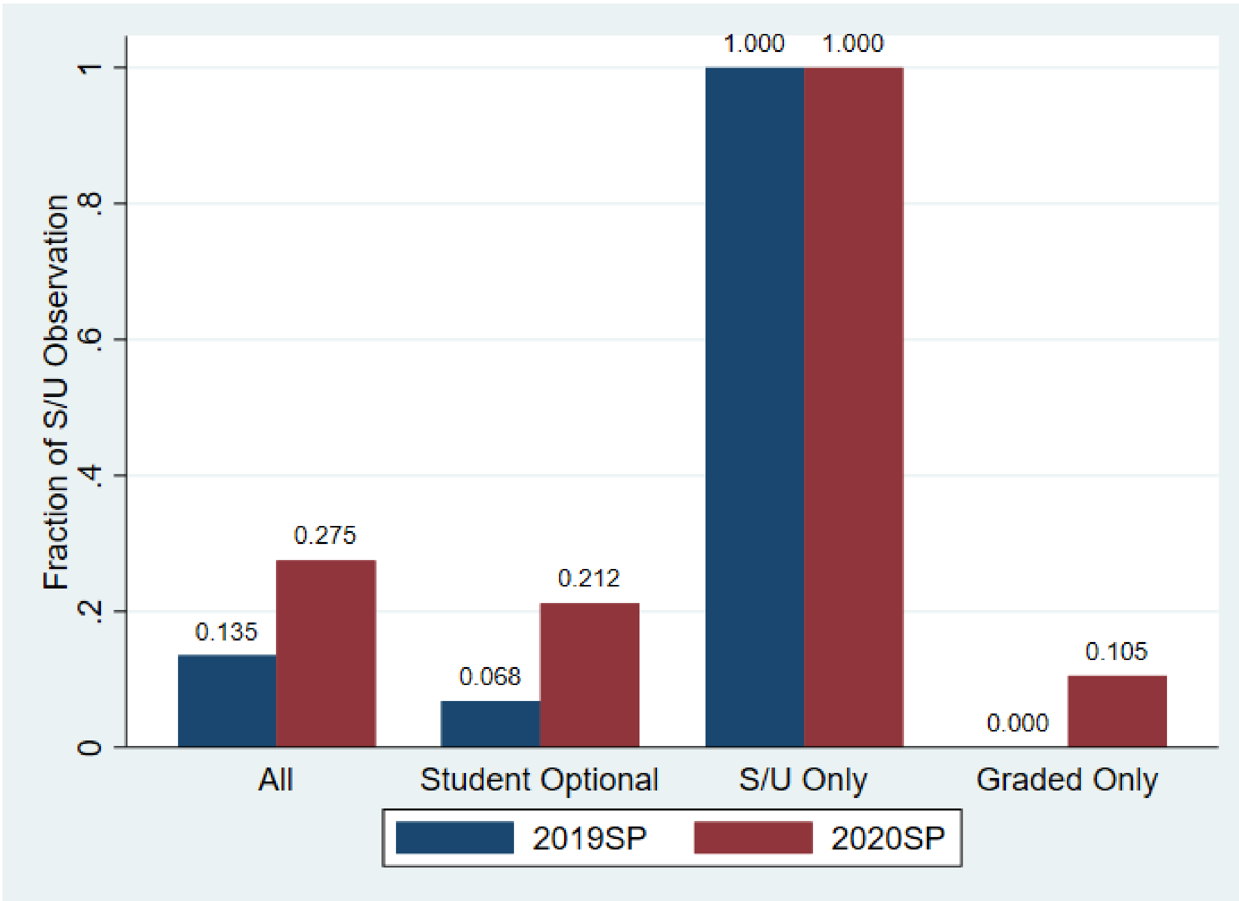
In the spring semester of 2020, university campuses were closed and university administrations provided a myriad of accommodations to assist students weathering the COVID19 pandemic. Extending the deadline for the S / U option provided students with the option to continue taking a class without a grade penalty even when the home environment presents learning challenges. This paper aims to better understand the characteristics of the users of the S/U option and in particular the role of the return home treatment on S/U uptake, relative to other more grade preference-related causes. We use administrative data from Cornell University to causally uncover the sources of S/U choices and S/U switches in the Spring 2020 semester. We use a generalized difference-in-difference estimation strategy to ascertain the role of a student-specific return home treatment, guided by the predictions of a theoretical model of grade option choices. We find that the return home treatment had a significant effect on students' decisions to switch the grading option to S/U. We also demonstrate that the story is nuanced, as a list of non-causal but informative factors is shown to be correlated with S/U uptake. These include nonlinear grade opportunism effects, class size, student seniority, gender, major (e.g., business-related and STEM), and peer group effects from students of the same gender and ethnicity in the same class.

Female, non-URM, and non-STEM students were more responsive to changes in instruction modalities during the pandemic in their S/U choices and switches. Our investigation suggests that there are causes related to both grade preference and career norms that may naturally have led to disproportionate responses. Thus, the lesson to take away for future emergency planning is that the uptake of student accommodations during a pandemic cannot easily be divorced from the pursuit of better grades, career demands, in addition to challenges associated with online learning.

Although the role of peer support in the in-person classroom has been much studied, the role of friendship in an online environment, where students are physically at a distance from one another, is an understudied topic. We track down student-course level friendship networks by counting the number of same high school and same Greek chapter students in a class. We find that the S/U choice and switch decisions of students with at least one friend in a class are no longer subject to the severity of the return home shock. We provided a thorough look at the mechanisms of such a link, and conclude that evidence strongly point to remote friendship as a source of academic support particularly when poor internet access makes online learning even more challenging. The COVID19 experience provided a unique opportunity to gauge the sources of learning challenges with online instruction during a pandemic and deepened our understanding about the importance of peers in virtual classroom settings.

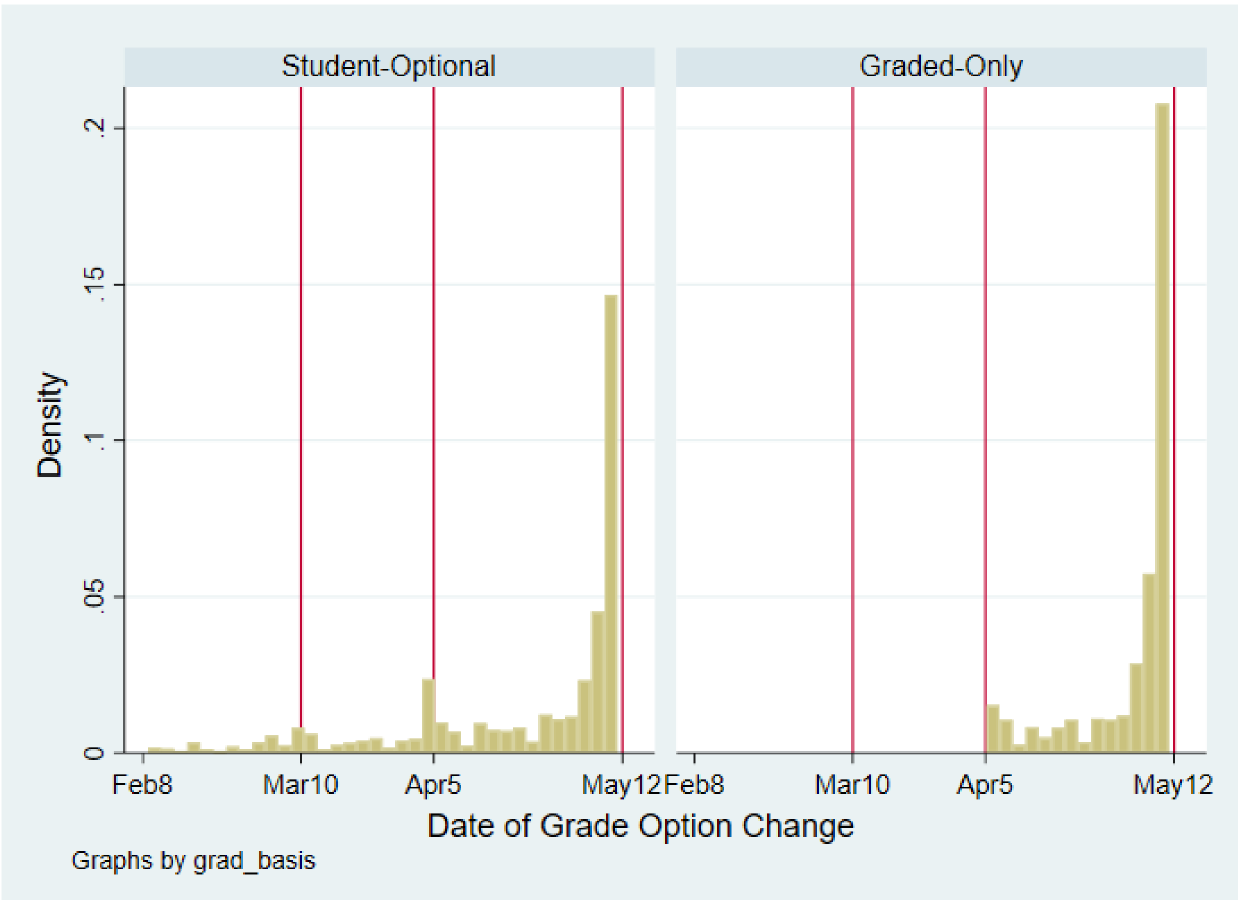
Figures

Figure 1: S/U Option Change by Course Type



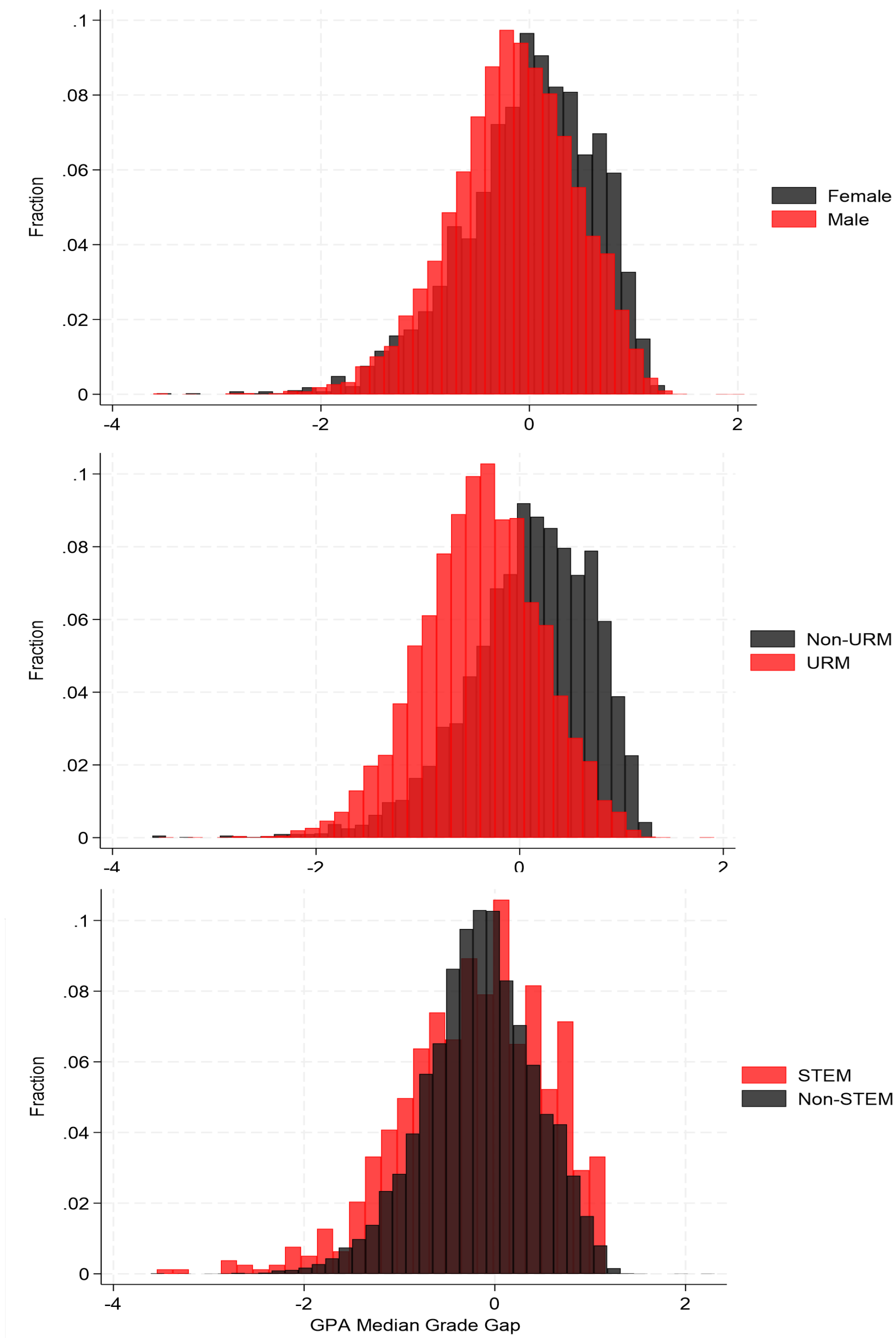
Notes: This figure shows the fraction of student-course level observations taken using S/U for Spring 2019 and Spring 2020 by course types: student optional, S/U only, and graded only. The blue bars represent the fraction of student-course level observations taken using S/U for Spring 2019 for all courses, student optional courses, S/U only courses, and graded only courses. The red bars represent corresponding fractions for spring 2020.

Figure 2: S/U Option Change by Date



Notes: This figure shows a density plot of students' S/U switch behavior by days of the semester from the first day of Spring 2020 semester Feb 6, 2020 to the last before students have to petition to switch grading option May 12, 2020. The left panel shows the results for student-optional courses, and the right panel shows the results for graded-only courses. The two red vertical lines represent March 10, the day when "return-home" order was announced, and April 5, 2020, the first day of virtual instruction

Figure 3: GPA Median Grade Gap Distribution by Gender, URM and STEM Major



Notes: This figure shows histograms of the GPA-Median Grade Gap (= student cumulative GPA in Fall 2019 − past median grade of the class) distributions among freshman students in Spring 2020. The figures are plotted by gender, URM, and STEM major choices.

Tables

Table 1: Summary Statistics: by Course

	(1) All		(2) Student-Optional		(3) Graded-Only		(4) S/U-Only	
	mean	sd	mean	sd	mean	sd	mean	sd
Past S/U Fraction	0.213	0.389	0.133	0.269	0.000	0.000	1.000	0.000
Fraction using S/U Sp '20	0.298	0.362	0.225	0.280	0.119	0.154	1.000	0.000
Past Median Course Grade	3.792	0.346	3.779	0.367	3.807	0.319		
Median Course Grade	3.955	0.236	3.954	0.245	3.956	0.221		
Number of Student in Class	27.925	53.728	26.459	54.251	34.576	56.878	17.568	40.621
Course Level								
1000-2000	0.186	0.389	0.098	0.297	0.158	0.365	0.574	0.495
2000-3000	0.160	0.366	0.173	0.378	0.183	0.387	0.057	0.233
3000-4000	0.183	0.387	0.216	0.412	0.185	0.389	0.057	0.233
4000+	0.471	0.499	0.513	0.500	0.474	0.500	0.311	0.464
Observations	2328		1214		783		331	

Notes: This table shows summary statistics for all courses, student optional courses, graded-only courses, and S/U only courses

Table 2: Results on of S/U Choice By Class-Level with Friendship Controls

	(1) Freshmen	(2) Sophomore	(3) Junior	(4) Senior
Return-home Variables				
Standardized Distance to Ithaca	0.009**	0.007	-0.006	0.004
	(0.004)	(0.005)	(0.005)	(0.006)
Internet Coverage	-0.114**	-0.023	0.015	-0.027
	(0.053)	(0.049)	(0.062)	(0.070)
LEX COVID Exposure	0.003	0.010*	-0.006	-0.000
	(0.005)	(0.006)	(0.006)	(0.007)
Student x Course Variables				
Cumulative GPA (FA19)	-0.057***	-0.086***	-0.090***	-0.032
	(0.019)	(0.028)	(0.031)	(0.031)
Past Course Median	-0.111***	-0.286***	-0.250***	-0.173***
	(0.024)	(0.030)	(0.034)	(0.032)
GPA-Median Gap Quintile				
2	0.042**	0.038*	0.024	0.005
	(0.020)	(0.020)	(0.022)	(0.021)
3	0.084***	0.050*	0.055*	0.046*
	(0.025)	(0.027)	(0.029)	(0.027)
4	0.074**	0.033	0.064*	0.039
	(0.030)	(0.034)	(0.037)	(0.033)
5	-0.011	-0.046	0.022	0.028
	(0.038)	(0.045)	(0.049)	(0.045)
Of own major	0.125	-0.135***	-0.042**	-0.052**
	(0.155)	(0.022)	(0.019)	(0.022)
Student Variables				
Female	-0.029***	-0.042***	-0.071***	-0.078***
	(0.009)	(0.010)	(0.011)	(0.011)
Ethnicity				
Other	0.044*	0.006	0.028	-0.047**
	(0.024)	(0.022)	(0.023)	(0.021)
Black	0.058**	-0.013	0.005	-0.019
	(0.026)	(0.025)	(0.023)	(0.024)
Asian	0.005	0.027*	0.019	-0.025*
	(0.013)	(0.014)	(0.014)	(0.014)
Hispanic	0.029	-0.010	0.025	-0.084***
	(0.032)	(0.030)	(0.033)	(0.027)
Multiple	0.021	-0.026	0.010	-0.032*
	(0.017)	(0.017)	(0.018)	(0.018)
Credit Taking	-0.007***	-0.007***	-0.000	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Log Family Income	0.002	-0.027**	-0.024**	0.009
	(0.010)	(0.011)	(0.012)	(0.012)
N	12788	13154	11496	12726

Table 2 continued from previous page

	(1) Freshmen	(2) Sophomore	(3) Junior	(4) Senior
Course Variables				
Past Course S/U Fraction	0.172***	0.038	-0.092	0.077
	(0.064)	(0.060)	(0.057)	(0.050)
Number of Students in Class	0.000**	0.000*	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Course Level				
2000-3000	0.072***	0.053***	-0.050***	-0.118***
	(0.010)	(0.013)	(0.018)	(0.018)
3000-4000	0.061**	0.060***	0.014	-0.122***
	(0.025)	(0.015)	(0.018)	(0.018)
4000+	0.129***	0.012	-0.077***	-0.128***
	(0.030)	(0.016)	(0.018)	(0.018)
Career Variables				
STEM Major	-0.044***	0.002	-0.005	-0.038***
	(0.013)	(0.010)	(0.011)	(0.011)
Business-related Major	0.128***	0.120***	0.066***	0.077***
	(0.018)	(0.016)	(0.016)	(0.014)
Group Variables				
Greek Life	0.032**	0.009	0.006	-0.018
	(0.016)	(0.015)	(0.015)	(0.014)
Fraction of same Gender Student in Class	-0.033	0.003	-0.083***	0.000
	(0.037)	(0.032)	(0.031)	(0.030)
Fraction of same Ethnicity Student in Class	-0.037	-0.024	0.032	-0.127***
	(0.053)	(0.047)	(0.046)	(0.040)
Number of Same-chapter Student in Class	-0.009**	-0.001	0.000	0.005*
	(0.005)	(0.004)	(0.004)	(0.003)
Number of Same-HS Students in Class	0.004	-0.011*	-0.014***	-0.003
	(0.004)	(0.006)	(0.005)	(0.006)
Time Variable				
After 04/05	0.030*	0.060***	0.129***	0.134***
	(0.018)	(0.020)	(0.022)	(0.025)
Constant	0.844***	1.942***	1.764***	1.193***
	(0.146)	(0.150)	(0.165)	(0.161)
N	12788	13154	11496	12726

Notes: This table shows estimated results of the impact of the ”return-home” treatment on student-level S/U uptake behavior for all student-optional courses for Spring 2020 by class level. The results are estimated using a linear probability model is applied. The four class levels are freshman, sophomore, junior, and senior. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 3: Results on of S/U Switch By Class-Level with Friendship Controls

	(1) Freshmen	(2) Sophomore	(3) Junior	(4) Senior
Return-Home Variables				
Standardized Distance to Ithaca	0.012**	0.009	-0.008	0.010
	(0.005)	(0.006)	(0.006)	(0.007)
Internet Coverage	-0.103*	0.023	0.044	-0.018
	(0.060)	(0.058)	(0.076)	(0.083)
LEX COVID Exposure	0.004	0.014**	-0.008	0.003
	(0.005)	(0.007)	(0.007)	(0.008)
Student x Course Variables				
Cumulative GPA (FA19)	-0.009	-0.017	-0.027**	-0.018
	(0.007)	(0.010)	(0.012)	(0.015)
Past Course Median	-0.046***	-0.068***	-0.056***	-0.034**
	(0.009)	(0.012)	(0.013)	(0.015)
GPA-Median Gap Quintile				
2	0.005	0.011	0.015*	-0.006
	(0.008)	(0.007)	(0.009)	(0.010)
3	0.007	0.011	0.025**	0.008
	(0.010)	(0.010)	(0.012)	(0.013)
4	-0.001	0.015	0.029**	0.014
	(0.011)	(0.013)	(0.014)	(0.016)
5	-0.027*	-0.010	0.014	0.020
	(0.014)	(0.017)	(0.019)	(0.022)
Of own major	-0.020*	-0.033***	-0.032***	-0.021**
	(0.012)	(0.006)	(0.007)	(0.010)
Student Variables				
Female	-0.005	-0.000	-0.022***	-0.031***
	(0.003)	(0.004)	(0.005)	(0.005)
Ethinicity				
Other	-0.006	0.002	-0.003	-0.016
	(0.008)	(0.008)	(0.010)	(0.010)
Black	-0.006	-0.009	0.004	-0.007
	(0.010)	(0.009)	(0.011)	(0.012)
Asian	-0.008*	-0.004	-0.010*	-0.015**
	(0.005)	(0.005)	(0.006)	(0.007)
Hispanic	-0.024**	-0.007	0.005	-0.025*
	(0.011)	(0.012)	(0.016)	(0.014)
Multiple	-0.003	-0.007	-0.007	-0.023***
	(0.006)	(0.006)	(0.008)	(0.008)
Credit Taking	-0.000	-0.000	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Log Family Income	0.001	-0.009**	-0.005	-0.009
	(0.003)	(0.004)	(0.004)	(0.006)
N	11863	11805	10319	11282

Table 3 continued from previous page

	(1) Freshmen	(2) Sophomore	(3) Junior	(4) Senior
Course Variables				
Past Course S/U Fraction	-0.008	0.006	0.028	0.018
	(0.015)	(0.016)	(0.021)	(0.018)
Number of Students in Class	-0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Course Level				
2000-3000	0.015***	0.029***	0.012*	-0.000
	(0.004)	(0.005)	(0.007)	(0.009)
3000-4000	-0.002	0.008	0.009	-0.010
	(0.007)	(0.005)	(0.007)	(0.009)
4000+	0.012	0.055***	0.048***	0.001
	(0.009)	(0.007)	(0.007)	(0.009)
Career Variables				
STEM Major	-0.016***	-0.003	0.003	-0.016***
	(0.005)	(0.004)	(0.005)	(0.005)
Business-related Major	-0.006	0.014**	0.016**	0.037***
	(0.005)	(0.006)	(0.007)	(0.008)
Group Variables				
Greek Life	0.022***	0.007	0.002	0.002
	(0.007)	(0.006)	(0.006)	(0.007)
Fraction of same Gender Student in Class	-0.027*	-0.004	-0.011	-0.003
	(0.014)	(0.012)	(0.014)	(0.015)
Fraction of same Ethnicity Student in Class	-0.032*	-0.019	-0.032	-0.047***
	(0.018)	(0.016)	(0.020)	(0.017)
Number of Same-chapter Student in Class	-0.004**	-0.004***	-0.000	0.002
	(0.001)	(0.001)	(0.002)	(0.002)
Number of Same-HS Students in Class	0.002	-0.004**	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.004)
Time Variable				
After 04/05	0.025	0.059***	0.143***	0.103***
	(0.019)	(0.023)	(0.026)	(0.030)
Constant	0.339***	0.385***	0.341***	0.447***
	(0.073)	(0.073)	(0.087)	(0.099)
N	11863	11805	10319	11282

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U switch behavior for all student-optional courses for Spring 2020 by class level. The results are estimated using a linear probability model. The four class levels are freshman, sophomore, junior, and senior. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 4: Results with Decomposition of R^2: S/U Choice (%)

	Variable Group						
	Return-home	Student x Course	Student	Course	Career	Group	Time
All	7.62	39.17	14.22	7.04	19.51	5.66	6.77
By Gender							
Female	8.97	32.17	12.45	9.87	19	12.08	5.47
Male	7.12	40.62	10.94	7	15.22	11.26	7.85
By STEM Major							
Non-STEM Major	8.15	42.01	15.21	5.93	16.89	5.24	6.56
STEM Major	6.06	19.8	22.81	31.79	1.1	14.22	4.23
By URM							
Non-URM	8.13	46.98	7.83	8	17.82	4.59	6.65
URM	8.99	26.46	7.96	6.68	27	13.26	9.64

Notes: This table shows Shapley values when estimating the contributions of seven categories of variables to students S/U switch decisions in Spring 2020 for student-optional courses. The seven categories include: return-home variables, student-course variables, student variables, course variables, career variables, group variables, and time indicator. In addition to decomposing Shapley variables for all students, we also do so by student characteristics including gender, STEM major, and URM status.

Table 5: Results with Decomposition of R^2: S/U Switch (%)

	Variable Group						
	Return-home	Student x Course	Student	Course	Career	Group	Time
All	38.37	17.15	1.88	.93	2.13	3.8	35.73
By Gender							
Female	42.11	14.98	1.57	1.83	.9	6.9	31.7
Male	33.75	18.47	3.99	.52	3.3	2.64	37.33
By STEM-Major							
Non-STEM Major	37.15	20.75	2.08	1.17	.86	3.91	34.08
STEM Major	31.10	14.91	14.77	2.86	2.02	8.45	25.89
By URM							
Non-URM	37.09	22.55	.42	1.08	1.65	5.21	32.01
URM	37.45	11.48	3.72	.69	3.16	2.25	41.25

Notes: This table shows Shapley values when estimating how seven categories of variables contribute to students S/U switch decisions in Spring 2020 for student-optional courses. The seven categories of variables include: return-home variables, student-course variables, student variables, course variables, career variables, group variables, and time indicator. In addition to decomposing Shapley variables for all students, we also do so by student characteristics including gender, STEM major, and URM status.

Table 6: Heterogeneous Return-Home Effects on S/U Choice Among Freshmen with Social Network Controls

	Gender		STEM-Major		URM	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Non-STEM	STEM	Non-URM	URM
Standardized Distance to Ithaca	0.020***	-0.002	0.010**	0.003	0.014***	-0.007
	(0.006)	(0.007)	(0.005)	(0.014)	(0.005)	(0.009)
Internet Coverage	-0.217***	-0.006	-0.162***	0.121	-0.145**	-0.034
	(0.073)	(0.077)	(0.059)	(0.114)	(0.067)	(0.092)
LEX COVID Exposure	0.013**	-0.008	0.004	-0.003	0.007	-0.008
	(0.006)	(0.007)	(0.005)	(0.016)	(0.005)	(0.011)
N	6728	6060	11382	1406	9436	3352

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U uptake behavior for all student-optional courses for Spring 2020 for Freshmen. The results are estimated using a linear probability model. We divide students into male and female students, STEM and non-STEM students, as well as URM and non-URM students. All student-, course-, student-course, career-, group and time variables are included. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 7: Heterogeneous Return-Home Effects on S/U Switch Among Freshmen with Social Network Controls

	Gender		STEM-Major		URM	
	(1)	(2)	(3)	(4)	(5)	(6)
	Female	Male	Non-STEM	STEM	Non-URM	URM
Return-Home Variables						
Standardized Distance to Ithaca	0.020***	0.002	0.012**	0.011	0.016***	-0.002
	(0.007)	(0.007)	(0.005)	(0.015)	(0.006)	(0.010)
Internet Coverage	-0.226***	0.034	-0.147**	0.061	-0.112	-0.052
	(0.085)	(0.084)	(0.069)	(0.103)	(0.072)	(0.110)
LEX COVID Exposure	0.011*	-0.003	0.005	0.006	0.006	-0.000
	(0.006)	(0.008)	(0.005)	(0.018)	(0.005)	(0.012)
N	6296	5567	10535	1328	8811	3052

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U switch behavior for all student-optional courses for Spring 2020 for Freshmen. The results are estimated with a linear probability model. We divide students into male and female students, STEM and non-STEM students. All student-, course-, student-course, career-, group and time variables are included. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 8: S/U Uptake and S/U Switch Determinants: The Post-Return Home Effect of Remote Friendship with Course Fixed Effects

S/U Uptake	All	Female	Non-URM	Non-STEM
Standardized Distance to Ithaca	0.009**	0.019***	0.016***	0.010**
	(0.005)	(0.006)	(0.005)	(0.005)
Internet Coverage	-0.117**	-0.215***	-0.155**	-0.167***
	(0.054)	(0.074)	(0.069)	(0.060)
Friends × Post	-0.015**	-0.022***	-0.019***	-0.019***
	(0.006)	(0.008)	(0.007)	(0.007)
Observations	12788	6728	9436	11382
R^2				

S/U Switch	All	Female	Non-URM	Non-STEM
Standardized Distance to Ithaca	0.012***	0.021***	0.016***	0.013**
	(0.005)	(0.006)	(0.005)	(0.005)
Internet Coverage	-0.114*	-0.232***	-0.119*	-0.154**
	(0.059)	(0.082)	(0.071)	(0.067)
Friends × Post	-0.014***	-0.016**	-0.016***	-0.015***
	(0.005)	(0.007)	(0.006)	(0.005)
Observations	11863	6296	8811	10535

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U Choice behavior for all student-optional courses for Spring 2020 by class level. The results are estimated using a linear probability model as in Table A3 and A4. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. "Friends" is a binary variable valued at unity if a student has at least one friend in the class, and zero otherwise. "Post" is a binary variable value at unity for $t = 2$, and zero other. "Friends x Post" is the interaction term. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 9: Results on S/U Choice for Freshman Subgroups and Course Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Female		Non-STEM		Non-URM	
	At Least One Friend	No Friends	At Least One Friend	No Friends	At Least One Friend	No Friends
Panel A: Same High School						
Standardized Distance to Ithaca	0.002	0.022***	-0.006	0.012**	0.007	0.016***
	(0.016)	(0.007)	(0.013)	(0.005)	(0.014)	(0.005)
Internet Coverage	-0.210	-0.211**	-0.127	-0.168**	-0.122	-0.141*
	(0.155)	(0.082)	(0.124)	(0.067)	(0.122)	(0.081)
Past Course Median	-0.044	-0.130***	-0.006	-0.130***	0.047	-0.118***
	(0.080)	(0.032)	(0.069)	(0.029)	(0.072)	(0.030)
Observations	1402	5326	2360	9022	2172	7264
Panel B: Same Greek Chapter						
Standardized Distance to Ithaca	0.018	0.021***	0.022*	0.008	0.030**	0.012**
	(0.016)	(0.006)	(0.012)	(0.005)	(0.013)	(0.006)
Internet Coverage	-0.008	-0.274***	0.110	-0.224***	0.115	-0.212***
	(0.181)	(0.079)	(0.152)	(0.064)	(0.138)	(0.076)
Past Course Median	-0.128	-0.109***	-0.023	-0.126***	-0.061	-0.098***
	(0.090)	(0.032)	(0.073)	(0.029)	(0.076)	(0.030)
Observations	1386	5342	2246	9136	2062	7374
Panel C: Same High School or Same Greek Chapter						
Standardized Distance to Ithaca	0.015	0.023***	0.014	0.010*	0.025**	0.011*
	(0.012)	(0.007)	(0.009)	(0.005)	(0.010)	(0.006)
Internet Coverage	-0.174	-0.248***	-0.072	-0.218***	-0.084	-0.193**
	(0.131)	(0.087)	(0.105)	(0.071)	(0.103)	(0.089)
Past Course Median	-0.077	-0.120***	-0.034	-0.135***	-0.022	-0.111***
	(0.062)	(0.034)	(0.052)	(0.031)	(0.055)	(0.032)
Observations	2428	4300	4042	7340	3684	5752

Notes: This table shows estimated results of the impact of the ”return-home” treatment on S/U choice behavior for student-optional courses in Spring 2020 among three freshman student subgroups: female students, non-STEM students and non-URM students. The results are estimated using a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 10: Results on S/U Switch for Freshman Subgroups and Course Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Female		Non-STEM		Non-URM	
	At Least One Friend	No Friends	At Least One Friend	No Friends	At Least One Friend	No Friends
Panel A: Same High School						
Standardized Distance to Ithaca	0.006	0.022***	-0.003	0.014**	0.010	0.017***
	(0.017)	(0.007)	(0.014)	(0.006)	(0.015)	(0.006)
Internet Coverage	-0.096	-0.257***	-0.095	-0.153*	-0.096	-0.094
	(0.168)	(0.097)	(0.145)	(0.078)	(0.135)	(0.085)
Past Course Median	-0.064**	-0.047***	-0.051*	-0.052***	-0.066**	-0.045***
	(0.027)	(0.013)	(0.029)	(0.011)	(0.026)	(0.011)
Observations	1309	4987	2180	8355	2021	6790
Panel B: Same Greek Chapter						
Standardized Distance to Ithaca	0.015	0.021***	0.018	0.011**	0.028*	0.014**
	(0.018)	(0.007)	(0.014)	(0.006)	(0.014)	(0.006)
Internet Coverage	0.008	-0.288***	0.228	-0.234***	0.210	-0.194**
	(0.171)	(0.094)	(0.151)	(0.076)	(0.149)	(0.081)
Past Course Median	0.007	-0.056***	-0.003	-0.060***	-0.001	-0.056***
	(0.033)	(0.013)	(0.028)	(0.011)	(0.029)	(0.011)
Observations	1291	5005	2072	8463	1917	6894
Panel C: Same High School or Same Greek Chapter						
Standardized Distance to Ithaca	0.016	0.022***	0.014	0.012**	0.026**	0.013**
	(0.014)	(0.007)	(0.011)	(0.006)	(0.011)	(0.006)
Internet Coverage	-0.132	-0.276***	0.001	-0.226***	-0.034	-0.157*
	(0.141)	(0.104)	(0.117)	(0.084)	(0.115)	(0.092)
Past Course Median	-0.030	-0.055***	-0.024	-0.061***	-0.029	-0.051***
	(0.022)	(0.015)	(0.022)	(0.012)	(0.020)	(0.012)
Observations	2261	4035	3728	6807	3430	5381

Notes: This table shows estimated results of the impact of the ”return-home” treatment on S/U switch behavior for student-optional courses in Spring 2020 among three freshman student subgroups: females students, Non-STEM students, and Non URM students. The results are estimated with a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 11: Spring 2020 Grade Determinants with Course Fixed Effects: The Role of Remote Friendship

	(1) All Classes	(2) All Classes	(3) Freshman Class	(4) Freshman Class
Standardized Distance to Ithaca	-0.001	0.000	0.001	0.003
	(0.003)	(0.004)	(0.006)	(0.007)
Internet Coverage	0.204***	0.267***	0.331**	0.386***
	(0.064)	(0.070)	(0.130)	(0.140)
Friends	0.026***	0.351***	0.056***	0.431**
	(0.008)	(0.0 91)	(0.015)	(0.182)
Friends ×		-0.041***		-0.062**
Past Median Grade		(0.014)		(0.026)
Observations	39450	39450	10300	10300
R^2	0.371	0.372	0.398	0.399

Notes: This table shows the determinants of end-of-semester grades in Spring 2020 for all student-optional courses for Spring 2020. The results are estimated with a linear probability model. Results for all student-course observations, as well as for freshmen student-course observations are shown. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. "Friends" is a binary variable, with unit value when the student has at least one friend in class, and zero otherwise. Friends × Standardized distance from campus, as well as Friends × internet access are also included as additional controls in columns (2) and (4). Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table 12: Summary Statistics: Correlates of Friendship

	(1) All	(2) ≥ 1 Friend	(3) No Friends	(4) ≥ 1 Friend Female	(5) No Friends Female	(6) ≥ 1 Friend Non-URM	(7) No Friends Non-URM	(8) ≥ 1 Friend Non-STEM	(9) No Friends Non-STEM
Average Distance to Ithaca (miles)	907.961	764.122	980.295	745.372	952.334	688.161	955.978	790.395	1017.148
Average Internet Access	0.891	0.896	0.889	0.897	0.886	0.902	0.900	0.899	0.891
Female Share	0.554	0.572	0.545	1.000	1.000	0.587	0.563	0.569	0.544
URM Share	0.269	0.196	0.306	0.176	0.283	0.000	0.000	0.192	0.293
STEM Major Share	0.131	0.127	0.133	0.132	0.134	0.123	0.117	0.000	0.000
Average GPA Course Median Gap	-0.127	-0.022	-0.184	-0.045	-0.185	0.034	-0.070	-0.002	-0.139
Observations	15902	5321	10581	3042	5764	4277	7345	4643	9174

Notes: This table shows summary statistics for all individuals in column 1. In addition, we break students into subgroups based on gender, URM and STEM classifications.

Online Appendix: A Conceptual Model of Grade Option Choice

We examine patterns of S/U option choice behavior in a model featuring (i) grading standards that are correlated with student ability and (ii) student preferences that are a function of grade ranks (e.g., Becker and Rosen, 1992; Betts, 1997; Oettinger, 2002; Dubey and Geanakoplos, 2010).

Let $\mathcal{G} \in [g^-, g^+]$ denote the range of feasible course grades. Suppose that individual student i's grade in course k ($g_{ik} \in \mathcal{G}$) relative to the course grade median ($g_{med,k}$) is a function of the student's grade ability in the course ($\gamma_{ik} \in \mathcal{G}$). γ_{ik} reflects the student's innate ability, accounting for course-specific features such as course difficulty, class size, and peer support for example:[38]

$$g_{ik} = g_{med,k} + f(\gamma_{ik} - g_{med,k}) - \lambda_{ik} + \epsilon \tag{A1}$$

where the course grade mapping $f(\cdot)$ is defined on the range $[g^- - g_{med,k}, g^+ - g_{med,k}]$. We assume that the following properties of $f(\cdot)$ hold: (i) the median-ability student gets the median grade ($f(0) = 0$) on average, and (ii) higher ability students get higher grades ($f'(\cdot) \geq 0$). $f(\cdot)$ may be strictly convex or concave depending on whether grade ability exhibits increasing (decreasing) marginal returns if $f''(\cdot) > (\leq) 0$.

Returning home affects the expectation of course grade for students via the shifter λ_{ik}. Intuitively, a student with median grade ability no longer expects a median grade when $\lambda_{ik} > 0$ following the return home order. Naturally, students may also have expectations about possible grade accommodations during a pandemic, which helps offset the grade impact of learning challenges associated with online instruction. Since we will not be able to separately identify these two opposing forces at the student-course level in our empirical work, we thus think of λ_{ik} as the net effect (grade penalties due to online learning barriers net of grade inflation) of the return-home order on grade expectations. In effect, if we find evidence supporting $\lambda_{ik} > 0$ and grade inflation was present, then the actual effect of learning barriers S/U been even higher. Finally, ϵ is a random error term with zero mean due, for example, to exam performance or grading that may happen with error.

Taking course k for a grade increases the student's cumulative GPA going forward, on average, if

$$c_i < g_{med,k} + f(\gamma_i - g_{med,k}) - \lambda_{ik}.$$

Beyond grade opportunism, student preference regarding the S/U option may also embody personal preference, or major-specific norms about the ability-signaling role of an S/U grade. Thus, we assume that a student will prefer the S/U option if and only if

$$c_i \geq g_{med,k} + f(\gamma_i - g_{med,k}) - \lambda_{ik} + \eta_{ik}. \tag{A2}$$

$\eta_{ik} \in \mathbb{R}$, known to the student, denote a non-grade related S/U option preference shifter. If large enough, a student may not be inclined to take an S / U course even if doing so can avert a cumulative reduction in GPA after taking a class. Such preference for a graded option may depend, for example, on career, major and/or course-level norms, risk preferences, and years until graduation. We let this vector of non-grade related S/U triggers be denoted as $\mathbf{n_{ik}}$ for student i, and $\nu(\eta_{ik}, \mathbf{n_{ik}})$ be the cumulative distribution function of the preference shifter η_{ik} for student i in period 0.

We assume that the grade ability of the student in a course is jointly determined by (i) the

[38] Course grades will also depend on effort and study time. We think of γ_{ik} as the optimized grade ability of a student accounting for effort cost.

overall academic ability of a student as summarized by the cumulative grade point average (GPA) of the student g_i^{av} up until the current term, and (ii) the combined effect of a vector of other determinants $\mathbf{G_i}$ including a student's own characteristics (g_i^o), course-specific determinants (g_i^c), and peer group triggers (g_i^n). Let $\theta \in [0,1]$ denote the relative importance of the cumulative GPA as a factor in determining new course grades:

$$\begin{aligned}\gamma_i - g_{med,k} &= \theta(c_i - g_{med,k}) + (1-\theta)(g_i^o + g_i^c + g_i^n - g_{med,k}) \\ &\equiv \theta(c_i - g_{med,k}) + (1-\theta)(G_i - g_{med,k}). \end{aligned} \tag{A3}$$

The probability that a student will take a course S/U, ρ_{ik} is

$$\begin{aligned}\rho_{ik} &= Prob\left(\eta_{ik} \le \lambda_{ik} + c_i - g_{med,k} - f(\theta(c_i - g_{med,k}) + (1-\theta)(G_{ik} - g_{med,k}))\right) \\ &= \nu\left(\lambda_{ik} + c_i - g_{med,k} - f(\theta(c_i - g_{med,k}) + (1-\theta)(G_{ik} - g_{med,k})),\ \mathbf{n_{ik}}\right), \end{aligned} \tag{A4}$$

Approximating linearly, we model the likelihood of choosing the S/U option in period t, as:

$$\rho_{ik} = \beta_o + \beta_\lambda \cdot \lambda_{ik} + \beta_c c_i + \beta_m \cdot g_{med,k} + \beta_g \cdot \varphi(c_i - g_{med,k}) + \beta_{\mathbf{G}} \cdot \mathbf{G_{ik}} + \beta_{\mathbf{n}} \cdot \mathbf{n_{ik}} + D_t \tag{A5}$$

where β_λ is our coefficient of interest associated with the return home treatment variable λ_{ik}. β_c is the effect of cumulative GPA on S/U uptake, while β_m captures the extent to which the median grade of a course affects S/U uptake. $f(c_i - g_{med,k})$ is potentially a nonlinear function in $c_i - g_{med,k}$ indicating the interactive effects of cumulative GPA and median grade. It is concave (convex) whenever a students' grade ability exhibits increasing (diminishing) marginal returns. $\beta_{\mathbf{G}}$ is a coefficient vector corresponding to the effect of student characteristics (g_i^o), course-specific determinants (g_i^c), and peer group triggers (g_i^n) on S/U uptake. β_n is the career effect coefficients associated with the preference shifters $\mathbf{n_{ik}}$. Finally, D^t is a time period fixed effect. Altogether, these are the seven groups of variables we take into account in our empirical specifications (return home variables (λ_{ik}), student-course characteristics ($c_i - g_{med,k}$), student characteristics (g_i^o), course characteristics (g_i^c), group characteristics (g_i^n), career effects ($\mathbf{n_{ik}}$), and time effects (D_t)).

The predictions in equation (A5) can be succinctly summarized as follows: the likelihood that a student chooses the S/U option, all else constant (i) increases with any challenges to grade expectations due to the return home treatment, $\lambda_{ik} > 0$, (ii) decreases with increases with the median grade of the course, $g_{med,k}$, (iii) decreases with student-, course- and group-factors that improves a student's grade potential ($\mathbf{G_{ik}}$), and (iv) increases with student individual or career characteristics that value the relative certainty of an S/U grade, $\mathbf{n_{ik}}$.

In addition, if the student grade potential exhibits increasing marginal grade returns and $\theta > 0$, (v) students with intermediate levels of cumulative GPA take the S/U option, while (vi) students with the highest and the lowest levels of cumulative GPA take the graded option.

To see that (v) and (vi) hold, let $\delta^i \equiv c^i - g^i_{med,k}$, $i = 1, 2$. Suppose $\delta^1 - f(\theta\delta^1 + (1-\theta)(G_{ik} - g_{med,k})) = \delta^2 - f(\theta\delta^2 + (1-\theta)(G_{ik} - g_{med,k}))f(\tilde{\delta}) = \lambda_{ik} - \eta_{ik}$. By convexity of $f(\cdot)$, $\delta - f(\theta\delta + (1-$

$\theta)(G_{ik} - g_{med,k}))$ is concave in δ. Thus, for any $\sigma \in (0,1)$, and any $\delta^\sigma = \sigma\delta^1 + (1-\sigma)\delta^2$

$$\begin{aligned} & \lambda_{ik} - \eta_{ik} \\ = \; & \sigma[\delta^1 - f(\theta\delta^1 + (1-\theta)(G_{ik} - g_{med,k}))] + (1-\sigma)[\delta^2 - f(\theta\delta^2 + (1-\theta)(G_{ik} - g_{med,k}))] \\ = \; & \sigma\delta^1 + (1-\sigma)\delta^2 - \sigma f(\theta\delta^1 + (1-\theta)(G_{ik} - g_{med,k}))] + (1-\sigma)f(\theta\delta^2 + (1-\theta)(G_{ik} - g_{med,k})) \\ < \; & \delta^\sigma - f(\theta\delta^\sigma + (1-\theta)(G_{ik} - g_{med,k})). \end{aligned}$$

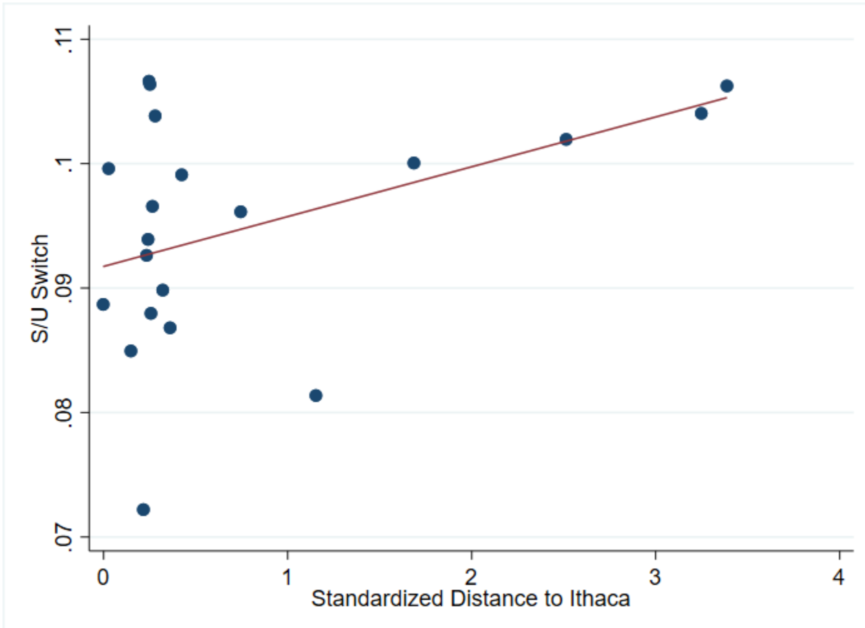
Or equivalently,

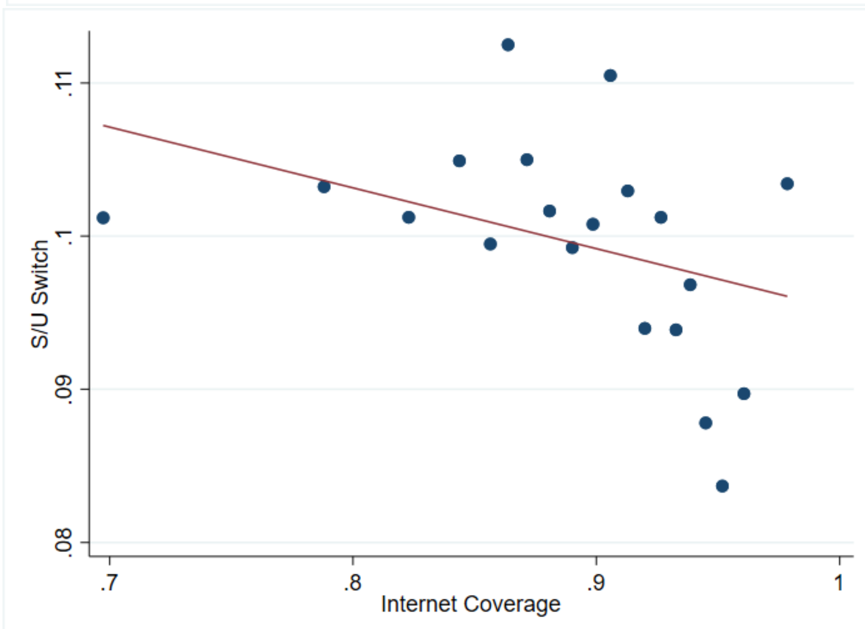
$$\lambda_{ik} - \eta_{ik} < \delta^\sigma - f(\theta\delta^\sigma + (1-\theta)(G_{ik} - g_{med,k})).$$

Thus from equation A2, students with intermediate levels of

Online Appendix Figures

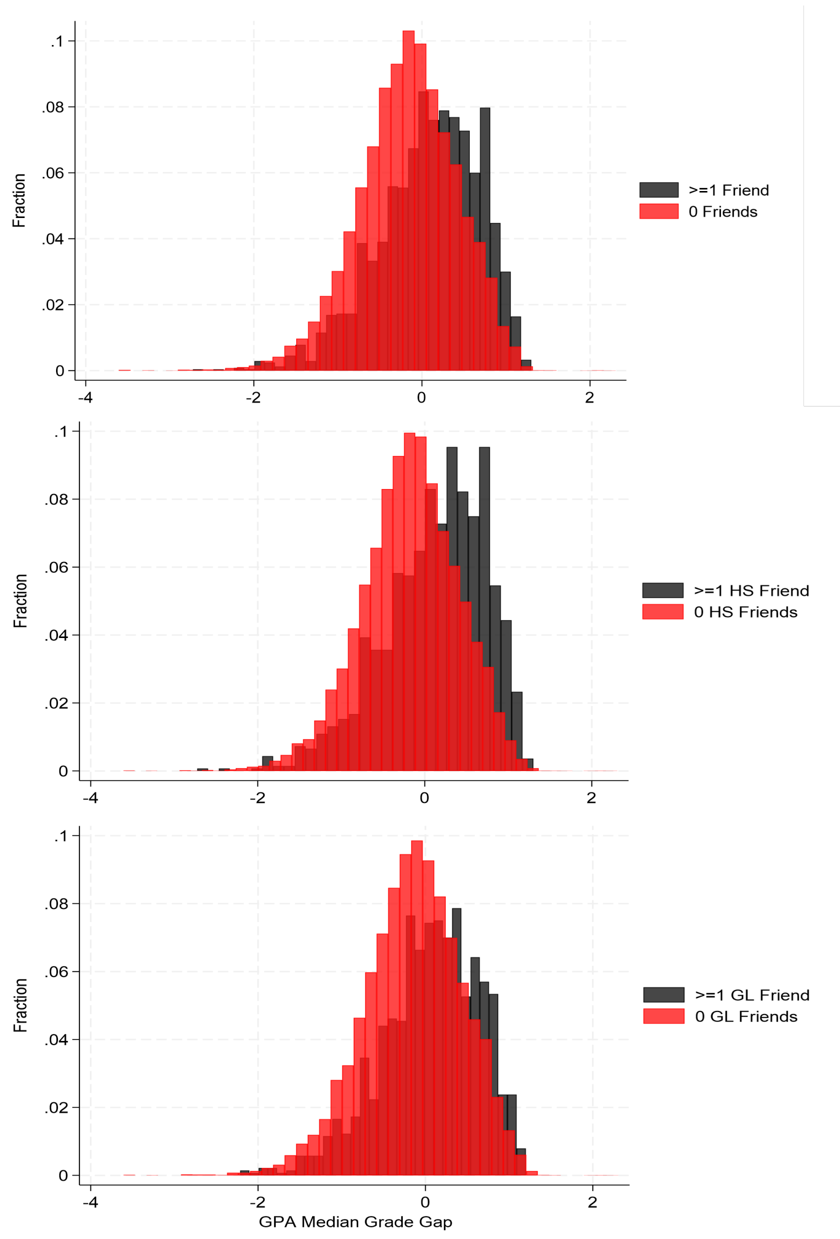
Figure A1: S/U Switch by Standardized Distance to Ithaca and by Internet Coverage





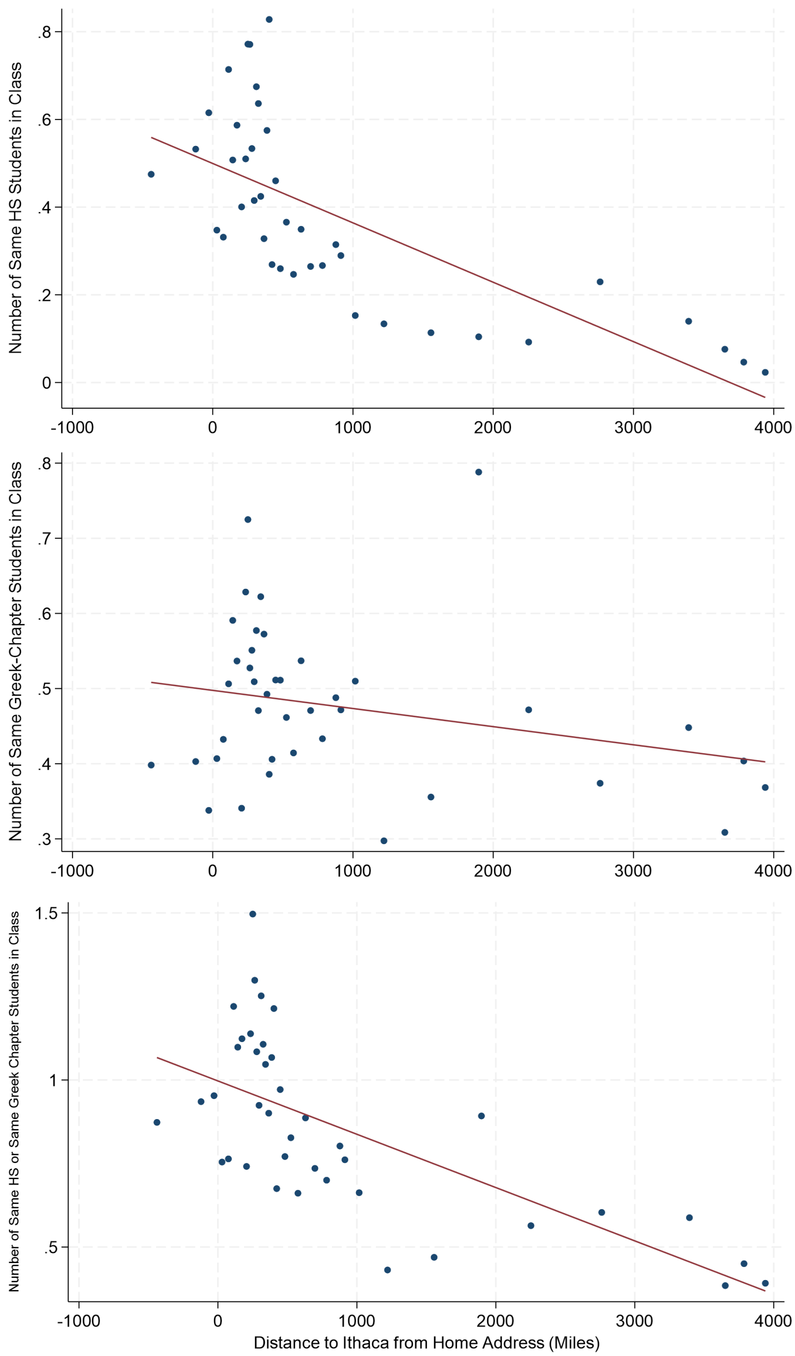
Notes: The top figure shows a binscatter plot for students' propensity to switch courses to S/U for all courses by (standardized) distance between their residence and Ithaca. The bottom figure shows a binscatter plot for students' propensity to switch courses to S/U for all courses by internet coverage in 2019 from the zip-code where the student's home residence is located. All students are equally divided into 20 bins. The vertical axis shows propensity to switch to S/U. A fitted line is plotted. All data is from Spring 2020.

Figure A2: GPA Median Grade Gap Distribution by Access to Friends in Class



Notes: This figure shows histograms of the GPA-Median Grade Gap (= student cumulative GPA in Fall 2019 − past median grade of the class) distributions among freshman students in Spring 2020. The figures are plotted by access to friends in class. "HS Friends" refers to student from the same high school in class. "GL Friends" refers to students in class in the same Greek chapter. "Friends" refers to either same high school or same Greek chapter friend.

Figure A3: Binscatter Plot Friendship in Class and Distance from Home Address Among Freshman Students



Notes: This figure shows binscatter plots for the number of friends (same high school, same Greek chapter, sum of same high school and same Greek chapter) in class by distance of home address from Ithaca in miles. Fitted lines are plotted with course fixed effects as controls. All data is from Spring 2020 for Freshman students only.

Online Appendix Tables

Table A1: Summary Statistics: by Individual

	(1) All		(2) With Class S/U		(3) With no Class S/U	
	mean	sd	mean	sd	mean	sd
Female	0.537	0.499	0.520	0.500	0.578	0.494
Ethnicity						
Other	0.264	0.441	0.264	0.441	0.266	0.442
White	0.395	0.489	0.388	0.487	0.412	0.492
Black	0.077	0.266	0.078	0.269	0.074	0.261
Asian	0.226	0.418	0.232	0.422	0.209	0.407
Hispanic	0.038	0.191	0.038	0.190	0.039	0.193
Multiple	0.000	0.000	0.000	0.000	0.000	0.000
Class-Level						
Freshman	0.229	0.420	0.255	0.436	0.162	0.368
Sophomore	0.264	0.441	0.239	0.427	0.326	0.469
Junior	0.239	0.427	0.222	0.416	0.283	0.451
Senior	0.268	0.443	0.283	0.451	0.229	0.420
Greek Life	0.263	0.440	0.263	0.440	0.264	0.441
STEM Major	0.376	0.484	0.370	0.483	0.392	0.488
Business-related Major	0.160	0.366	0.165	0.371	0.147	0.354
Log Family Income	11.455	0.449	11.452	0.449	11.463	0.450
Distance to Ithaca (miles)	923.215	1187.543	923.185	1189.118	923.292	1183.722
Internet Coverage (Share)	0.890	0.068	0.889	0.068	0.890	0.068
LEX COVID Exposure Index (April 2020)	0.778	0.473	0.778	0.472	0.777	0.473
LEX COVID Exposure Index (May 2020)	1.598	0.864	1.597	0.863	1.601	0.866
Cumulative GPA (FA 19)	3.441	0.465	3.427	0.463	3.476	0.469
Cumulative GPA (SP 20)	3.524	0.424	3.509	0.425	3.563	0.419
Credit Taking	16.336	2.814	16.428	2.851	16.103	2.705
Fraction of S/U credits from S/U only Courses	0.034	0.062	0.048	0.069	0.000	0.000
Fraction of S/U credits from Graded only Courses	0.124	0.191	0.172	0.206	0.000	0.000
Fraction of S/U credits from Student Optional Courses	0.174	0.231	0.243	0.240	0.000	0.000
Observations	12564		9002		3562	

Notes: This table shows summary statistics for all individuals in column 1. In addition, we break students into two groups: those who took at least one course S/U during Spring 2020 and those who took no course S/U during Spring 2020. We report results in column 2 and column 3

Table A2: Summary Statistics: by Individual for Student-optional Courses

	(1) All		(2) Student-Optional	
	mean	sd	mean	sd
Female	0.537	0.499	0.537	0.499
Ethnicity				
Other	0.264	0.441	0.263	0.441
White	0.395	0.489	0.394	0.489
Black	0.077	0.266	0.076	0.266
Asian	0.226	0.418	0.228	0.420
Hispanic	0.038	0.191	0.039	0.193
Multiple	0.000	0.000	0.000	0.000
Class-Level				
Freshman	0.229	0.420	0.231	0.422
Sophomore	0.264	0.441	0.259	0.438
Junior	0.239	0.427	0.238	0.426
Senior	0.268	0.443	0.271	0.445
Greek Life	0.263	0.440	0.259	0.438
STEM Major	0.377	0.481	0.383	0.483
Business-related Major	0.160	0.364	0.148	0.353
Family Income	11.455	0.449	11.454	0.450
Distance to Ithaca (miles)	923.215	1187.543	919.542	1186.149
Internet Coverage	0.890	0.068	0.890	0.068
Location Exposure Index (April 2020)	0.778	0.473	0.779	0.472
Location Exposure Index (May 2020)	1.598	0.864	1.599	0.863
Cumulative GPA (FA 19)	3.441	0.465	3.443	0.464
Cumulative GPA (SP 20)	3.524	0.424	3.524	0.423
Credit Taking	16.336	2.814	16.408	2.792
Fraction of Course S/U Switch Before 03/10	0.006	0.037	0.010	0.065
Fraction of Course S/U Switch 03/10-04/05	0.006	0.045	0.011	0.076
Fraction of Course S/U Switch 04/05-05/12	0.091	0.161	0.089	0.202
Observations	12564		11977	

Notes: This table shows summary statistics for all student-course level observations (column 1) and student-course level observations for all student-optional courses (column 2). Observations are grouped at the individual level.

Table A3: Results on S/U Option By Class-Level with Course Fixed Effects ($t = 0, 2$)

	(1) Freshman	(2) Sophomore	(3) Junior	(4) Senior
Standardized Distance to Ithaca	0.008*	0.007	-0.006	0.004
	(0.005)	(0.005)	(0.005)	(0.006)
Internet Coverage	-0.112**	-0.042	0.015	0.003
	(0.054)	(0.050)	(0.062)	(0.072)
Observations	12788	13154	11496	12726

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U Choice behavior for all student-optional courses for Spring 2020 by class level. The results are estimated using a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. The four class levels are freshman, sophomore, junior, and senior. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A4: Results on S/U Switch By Class-Level with Course Fixed Effects ($t = 0, 2$)

	(1) Freshman	(2) Sophomore	(3) Junior	(4) Senior
Standardized Distance to Ithaca	0.012**	0.008	-0.006	0.007
	(0.005)	(0.005)	(0.006)	(0.007)
Internet Coverage	-0.110*	0.004	0.032	-0.006
	(0.059)	(0.057)	(0.073)	(0.083)
Observations	11863	11805	10319	11282

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U switch behavior for all student-optional courses for Spring 2020 by class level. The results are estimated with a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. The four class levels are freshman, sophomore, junior, and senior. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A5: Results on S/U Choice and Switch for Second Semester Freshmen and First Semester Sophomores with Course Fixed Effects

	(1) Freshman 2nd Term, Choice	(2) Sophomore 1st Term, Choice	(3) Freshman 2nd Term, Switch	(4) Sophomore 1st Term, Switch
Standardized Distance to Ithaca	0.008*	0.031	0.012**	0.040
	(0.005)	(0.040)	(0.005)	(0.052)
Internet Coverage	-0.112**	0.194	-0.109*	0.374
	(0.054)	(0.297)	(0.059)	(0.552)
LEX COVID Exposure	0.002	0.047	0.004	0.059
	(0.005)	(0.041)	(0.005)	(0.054)
Observations	12762	380	11838	345

Notes: This table shows estimated results of the impact of the "return-home" treatment on S/U switch behavior for student-optional courses in Spring 2020 among second semester freshman students and first semester sophomore students. The results are estimated with a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A6: Results of Future Return Home Treatments on Pre-Online Instruction S/U Choice and S/U Switch with Course Fixed Effects

	(1) $t = 0$, SU Option	(2) $t = 0, 1$, SU Option	(3) $t = 0$, SU Switch	(4) $t = 0, 1$ SU Switch
Standardized Distance to Ithaca	-0.007	-0.007	-0.002*	-0.001
	(0.005)	(0.005)	(0.001)	(0.001)
Internet Coverage	-0.154	-0.154	-0.006	-0.002
	(0.094)	(0.094)	(0.011)	(0.014)
LEX COVID Exposure	-0.003	-0.003	-0.002*	-0.001
	(0.006)	(0.006)	(0.001)	(0.001)
Observations	12788	12788	6394	11892

Notes: This table shows estimated results of the impact of the future "return-home" treatment on freshman students S/U choice and S/U swtich behavior for all student-optional courses for Spring 2020 for two periods: the period before return home announcement (columns 1 and 3), and the periods before return home announcement, and the period after return home announcement but before online instruction (columns 2 and 4). The results are estimated with a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A7: Heterogeneou Return-Home Effect on S/U Choice Among Freshmen with Social Network and Course Fixed Effects

	(1) Female	(2) Male	(3) Non-URM	(4) URM	(5) Non-STEM	(6) STEM
Standardized Distance to Ithaca	0.018***	-0.002	0.009*	0.001	0.015***	-0.009
	(0.006)	(0.007)	(0.005)	(0.014)	(0.005)	(0.010)
Internet Coverage	-0.204***	-0.008	-0.158***	0.124	-0.154**	-0.021
	(0.074)	(0.079)	(0.060)	(0.118)	(0.069)	(0.095)
LEX COVID Exposure	0.010	-0.007	0.003	-0.005	0.007	-0.011
	(0.006)	(0.007)	(0.005)	(0.017)	(0.005)	(0.011)
Observations	6728	6060	11382	1406	9436	3352

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U choice behavior for all student-optional courses for Spring 2020 by gender, URM, and STEM major level. The results are estimated using a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A8: Heterogeneous Return-Home Effect on S/U Switch Among Freshmen with Social Network and Course Fixed Effects

	(1) Female	(2) Male	(3) Non-URM	(4) URM	(5) Non-STEM	(6) STEM
Standardized Distance to Ithaca	0.020***	0.002	0.012**	0.009	0.016***	0.002
	(0.006)	(0.007)	(0.005)	(0.014)	(0.005)	(0.010)
Internet Coverage	-0.226***	0.034	-0.147**	0.081	-0.118*	-0.064
	(0.082)	(0.082)	(0.069)	(0.100)	(0.071)	(0.109)
LEX COVID Exposure	0.011*	-0.005	0.005	0.003	0.005	0.005
	(0.006)	(0.008)	(0.005)	(0.017)	(0.005)	(0.012)
Observations	6296	5567	10535	1328	8811	3052

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U switch behavior for all student-optional courses for Spring 2020 by gender, URM, and STEM major level. The results are estimated using a linear probability model. All student-, course-, student-course, career-, group and time variables are included in addition to course fixed effects. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

Table A9: Heterogeneous S/U Choice and S/U Switch Results with and without Friends

	(1) ≥ 1 friend, S/U Option	(2) ≥ 1 friend, S/U Switch	(3) No friends, S/U Option	(4) No friends, S/U Switch	(5) ≥ 1 friend, S/U Option	(6) ≥ 1 friend, S/U Switch	(7) No friends, S/U Option	(8) No friends, S/U Switch
Return-Home Variables								
Standardized Distance to Ithaca	0.013	0.013	0.008	0.012**				
	(0.009)	(0.010)	(0.005)	(0.006)				
Time-zone to Ithaca					0.014*	0.015	0.006	0.009
					(0.008)	(0.009)	(0.005)	(0.005)
Internet Coverage	-0.012	0.069	-0.178***	-0.197**	-0.014	0.065	-0.171***	-0.189**
	(0.088)	(0.096)	(0.066)	(0.077)	(0.087)	(0.095)	(0.065)	(0.075)
LEX COVID Exposure	0.009	0.014	0.001	0.001	0.008	0.013	-0.002	-0.003
	(0.010)	(0.011)	(0.005)	(0.006)	(0.009)	(0.009)	(0.005)	(0.005)
Student x Course Variables								
Cumulative GPA	-0.156***	-0.065***	-0.029	0.008	-0.156***	-0.065***	-0.029	0.008
	(0.041)	(0.017)	(0.021)	(0.007)	(0.041)	(0.017)	(0.021)	(0.007)
Past Course Median	-0.051	-0.018	-0.123***	-0.051***	-0.051	-0.018	-0.123***	-0.051***
	(0.048)	(0.019)	(0.028)	(0.010)	(0.048)	(0.019)	(0.028)	(0.010)
GPA-Median Gap Quintile								
2	0.088**	0.031*	0.028	-0.005	0.088**	0.030*	0.028	-0.005
	(0.037)	(0.016)	(0.024)	(0.009)	(0.037)	(0.016)	(0.024)	(0.009)
3	0.156***	0.042**	0.063**	-0.002	0.155***	0.041**	0.063**	-0.002
	(0.048)	(0.019)	(0.029)	(0.011)	(0.048)	(0.019)	(0.029)	(0.011)
4	0.186***	0.061**	0.039	-0.021*	0.185***	0.061**	0.039	-0.021*
	(0.059)	(0.024)	(0.035)	(0.013)	(0.059)	(0.024)	(0.035)	(0.013)
5	0.129*	0.047	-0.049	-0.047***	0.128*	0.046	-0.049	-0.047***
	(0.077)	(0.032)	(0.044)	(0.016)	(0.077)	(0.032)	(0.044)	(0.016)
Of own major	0.069	-0.019	0.165	-0.016	0.069	-0.019	0.165	-0.015
	(0.260)	(0.031)	(0.193)	(0.010)	(0.261)	(0.032)	(0.193)	(0.010)
Student Variables								
Female	-0.027*	-0.006	-0.031***	-0.005	-0.027*	-0.006	-0.031***	-0.005
N	4550	4207	8238	7656	4550	4207	8238	7656

Table A9 continued from previous page

	(1) ≥ 1 friend, S/U Option	(2) ≥ 1 friend, S/U Switch	(3) No friends, S/U Option	(4) No friends, S/U Switch	(5) ≥ 1 friend, S/U Option	(6) ≥ 1 friend, S/U Switch	(7) No friends, S/U Option	(8) No friends, S/U Switch
	(0.016)	(0.006)	(0.011)	(0.004)	(0.016)	(0.006)	(0.011)	(0.004)
Ethnicity								
Other	0.065	-0.001	0.033	-0.009	0.065	-0.001	0.033	-0.009
	(0.041)	(0.014)	(0.030)	(0.010)	(0.041)	(0.014)	(0.030)	(0.010)
Black	0.033	-0.014	0.061**	-0.005	0.033	-0.014	0.061**	-0.004
	(0.054)	(0.019)	(0.030)	(0.011)	(0.054)	(0.020)	(0.030)	(0.011)
Asian	-0.014	-0.007	0.015	-0.009	-0.014	-0.007	0.016	-0.008
	(0.024)	(0.008)	(0.016)	(0.005)	(0.024)	(0.008)	(0.016)	(0.005)
Hispanic	0.111*	-0.039**	0.000	-0.017	0.111*	-0.039**	0.001	-0.016
	(0.068)	(0.018)	(0.035)	(0.013)	(0.068)	(0.018)	(0.035)	(0.013)
Multiple	0.013	-0.011	0.025	0.000	0.013	-0.010	0.025	0.001
	(0.031)	(0.011)	(0.020)	(0.008)	(0.031)	(0.011)	(0.020)	(0.008)
Credit Taking	-0.001	0.002	-0.009***	-0.001	-0.001	0.002	-0.009***	-0.001
	(0.004)	(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)
Family Income	-0.010	-0.006	0.010	0.006	-0.010	-0.006	0.011	0.006
	(0.018)	(0.005)	(0.013)	(0.004)	(0.018)	(0.005)	(0.013)	(0.004)
Course Variables								
Past Course S/U Fraction	0.119	-0.042	0.194**	0.007	0.119	-0.042	0.195**	0.007
	(0.114)	(0.027)	(0.078)	(0.018)	(0.114)	(0.027)	(0.078)	(0.018)
Number of Students in Class	0.000	-0.000**	0.000**	-0.000**	0.000	-0.000**	0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Course Level								
2000-3000	0.071***	0.016**	0.072***	0.013***	0.071***	0.016**	0.072***	0.013***
	(0.017)	(0.007)	(0.012)	(0.005)	(0.017)	(0.007)	(0.012)	(0.005)
3000-4000	0.023	-0.025**	0.073**	0.004	0.024	-0.025**	0.073**	0.004
	(0.045)	(0.010)	(0.029)	(0.009)	(0.045)	(0.010)	(0.029)	(0.009)
4000+	0.160**	0.016	0.119***	0.009	0.160**	0.016	0.119***	0.009
	(0.072)	(0.022)	(0.033)	(0.010)	(0.072)	(0.022)	(0.033)	(0.010)
Career Variables								
STEM Major	-0.056**	-0.029***	-0.039**	-0.009	-0.056**	-0.029***	-0.040**	-0.009
N	4550	4207	8238	7656	4550	4207	8238	7656

Table A9 continued from previous page

	(1) $\geq$ 1 friend, S/U Option	(2) $\geq$ 1 friend, S/U Switch	(3) No friends, S/U Option	(4) No friends, S/U Switch	(5) $\geq$ 1 friend, S/U Option	(6) $\geq$ 1 friend, S/U Switch	(7) No friends, S/U Option	(8) No friends, S/U Switch
	(0.022)	(0.008)	(0.017)	(0.006)	(0.022)	(0.008)	(0.017)	(0.006)
Business-related Major	0.140***	-0.004	0.122***	-0.006	0.140***	-0.004	0.122***	-0.006
	(0.026)	(0.007)	(0.024)	(0.006)	(0.026)	(0.007)	(0.024)	(0.006)
Group Variables								
Greek Life	0.040*	0.022**			0.039*	0.021**		
	(0.022)	(0.009)			(0.022)	(0.009)		
Fraction of same Gender	0.030	-0.018	-0.057	-0.031*	0.030	-0.019	-0.058	-0.032*
Student in Class	(0.068)	(0.024)	(0.044)	(0.017)	(0.068)	(0.024)	(0.044)	(0.017)
Fraction of same Ethnicity	0.025	-0.031	-0.063	-0.033	0.025	-0.032	-0.063	-0.033
Student in Class	(0.106)	(0.032)	(0.062)	(0.022)	(0.106)	(0.032)	(0.062)	(0.022)
Number of Same-chapter	-0.008*	-0.003*			-0.008*	-0.003*		
Students in Class	(0.005)	(0.002)			(0.005)	(0.002)		
Number of Same-HS	0.006	0.001			0.006	0.001		
Students in Class	(0.006)	(0.002)			(0.006)	(0.002)		
Time Variable								
After 04/05	0.032	0.038	0.022	0.013	0.054***	0.060***	0.042***	0.040***
	(0.034)	(0.037)	(0.021)	(0.023)	(0.020)	(0.022)	(0.013)	(0.014)
N	4550	4207	8238	7656	4550	4207	8238	7656

Notes: This table shows estimated results of the impact of the "return-home" treatment on students S/U choice and S/U switch behavior for all student-optional courses for Spring 2020 by subsample of student-course observations where the student has at least one high school or greek chapter friend in the class. The results are estimated with a linear probability model. Standard errors are clustered at individual-course level, and ***, **, * denote significance at 10%, 5%, and 1%.

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