Impacts of Online Instruction in Prerequisite Courses on Student Performance in Postrequisite Courses

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Abstract

Most research into the efficacy of online courses has focused on the difference in final grade outcomes between students who take a course online and those who take the same course in a face-to-face setting. In this paper, we consider the broader question of how participation in an online version of a prerequisite in a multi-course sequence ("upstream" courses) impacts students' grade outcomes in postrequisite ("downstream") courses, regardless of downstream modality.

We undertook this project using data gathered between 2019 and 2022, including the years surrounding a global historical event — the COVID-19 pandemic — that prompted an unprecedented increase in institutional commitment to online education necessitated by the exigencies of public health restrictions on in-person learning. To ensure a basic level of pedagogical quality, we included in our data set only courses that were purposefully designed with support from our institution's Teaching and Learning Center staff.

We found that the effect of upstream online course modality on downstream course outcomes is largely insignificant and that, where significant findings do exist, they generally show a slight advantage for students who took the online or hybrid version of an upstream course. We conclude that purposefully designed online courses can play a critical role in producing more equitable educational outcomes in terms of student success and in expanding access to higher education to students who might not otherwise be able to pursue it.

Introduction

While online learning in U.S. higher education has been expanding since the 1990s, the use of these modalities exploded during the COVID-19 pandemic as a result of the emergent impetus to keep education accessible during a global period of extended social isolation. Virtually every college and university in the United States found itself pivoting with head-spinning rapidity to remote synchronous and/or online asynchronous instruction. These transitions were frequently clunky and discomfiting, but they were born of necessity and thus generated unprecedented levels of institutional commitment.

The outcome of this mass natural experiment has generated two critical insights: first, many more faculty than pre-pandemic now appear to be at least receptive, if not outright enthusiastic, about conducting at least some of their teaching in online settings; and second, the increased accessibility of online educational opportunities has enabled many students who would otherwise be unable to pursue higher education due to logistical, family, work, or health considerations to enter, or remain in, school.

In short: the expansion of online learning has made higher education available to more people.

It does not necessarily follow, however, that online modalities represent an unalloyed good. For example, the speed with which the transition to online learning took place during the pandemic made it all but impossible for instructors with no online experience to purposefully design their courses in alignment with known best practices. Like in-person courses, online courses have also struggled with persistent equity gaps since well before the pandemic; perhaps because of their relative novelty, they tend to be viewed with more intrinsic suspicion. Meanwhile, in-person courses are assumed — mostly absent any rigorous investigation — to be of high quality sheerly on the basis of modality. Thus, this moment could be understood as one of tremendous opportunity: if institutions can harness the heightened visibility of online learning that came about because of the pandemic while also ensuring the delivery of a quality product that reduces equity gaps, online education could be made more accessible to the very students that colleges and universities are seeking to support in their educational endeavors — many of whom might not otherwise be able to attend at all.

The authors of this study are all affiliated or engaged, in various capacities, with the Teaching and Learning Center at the University of California, Santa Cruz. UC Santa Cruz is a medium-sized public institution serving approximately 19,000 students (all but about 2000 of whom are undergraduates). UCSC is an HSI (Hispanic-Serving Institution) and AANAPISI (Asian American and Native American Pacific Islander-Serving Institution) with a robust population of students who have transferred from community colleges and/or who are members of underrepresented groups, including racial/ethnic minorities (68.3%) and first-generation (FirstGen) students.

We undertook this investigation in order to ascertain the effectiveness of the online courses taught at our institution. While UCSC offered a small contingent of online courses pre-pandemic — some of which were designed with guidance from instructional designers affiliated with UCSC's Teaching and Learning Center — student interest in online courses increased (and has persisted) dramatically as a result of the pandemic. The university committees in charge of instruction did not greet the mere presence of student enthusiasm for online options as justification for expanding our roster of permanent offerings. Thus, we undertook this project as a systematic means of assessing the efficacy of our existing online courses — and, in particular, (A) the degree to which students in online "upstream" (prerequisite) courses fared in subsequent "downstream" postrequisites within course sequences, and (B) the degree to which the availability of upstream online courses impacted pre-existing equity gaps.

This project was initially conceived as an internal one. However, our preliminary search revealed that much of the extant literature is narrow in scope: the focus tends to be either a single class or class sequence, or reflections on the interventions of a single instructor. We failed to find the sort of larger-scale studies about short and/or "intermediate"-term outcomes (like grades) that could help us make a case for building out online programs without sacrificing quality; while some larger studies certainly exist, they tend to focus on time-to-degree and other longer-term outcomes rather than learning.

The pandemic, too, presented a kind of natural experiment, albeit a somewhat problematic one: while we had data from many more online courses to assess than we would have had prior to the pandemic, some of the courses were not purpose-designed in consultation with university instructional design staff. This study focuses on courses where the instructor *did* engage with instructional design staff — typically through a combination of small-group cohort learning and ongoing individual consultations — in intentionally designing the course for an online format. There was some variability in the level of instructor engagement, mostly centered around time commitment and differential ability to fully engage with course redesign for online modalities.

The result of our analysis was ultimately neither positive nor negative; on the contrary, it was notable primarily for its findings of statistical insignificance. Of 18 course sequences analyzed, 13 showed no significant difference in downstream course grades between students who took online vs. face-to-face upstream courses. Notably, in the remaining five course sequences, the tendency was for there to be significantly *better* outcomes for students taking the upstream course in an online modality (4 of 5), with one exception where in-person outcomes were better than that of hybrid offerings. This suggests that even minimally designed courses may be efficacious in moving students toward successful course completion and toward graduation, independent of demographic category. Highly designed courses would presumably be even more effective in doing so.

Our aim in this paper is to share our findings in the hope that large institutions beyond our campus may be able to use them to make evidence-based claims in service of expanding their online course offerings — and thus, to better meet students where they are in terms of providing them with meaningful opportunities to pursue higher education from which they would otherwise be shut out. Another aim was to expand the scope of the existing literature on online course efficacy; this is also the first study, to our knowledge, that investigates how course modality affects student outcomes in later courses, as opposed to comparing online vs. face-to-face performance within a single course.

Review of the Literature

Our search of the literature showed that results in online courses vary, sometimes quite dramatically, with regard to factors such as student characteristics, course design, and the concentration of online courses vs. face-to-face courses within a student's overall education program. The specific question that we attempt to answer in this study — the effect of upstream course modality on downstream course performance — is not addressed *per se*, but proxy data points help us to contextualize our results within the larger body of work in this area.

We identified the following four themes in the course of our review: (A) online courses show varying effects on persistence and success (as reflected by student course grades); (B) online courses have a generally positive effect on students' progression to transfer and graduation — in particular, when a student takes some, but not all, of their courses online; (C) individual student characteristics (e.g. demographics, experience taking previous online courses) may be a significant determinant of persistence, success in the course, and transfer/degree completion; and (D) design and context matter to student outcomes.

The assessment of this body of literature is somewhat complicated by missing information. In the same way that it is challenging to assess the pedagogical soundness of face-to-face courses absent a detailed description by the researcher, we found little in the way of pedagogical explanation of the design of the relevant courses in an overwhelming majority of the literature. Given the relative novelty and inconsistent deployment of online modalities across institutions, the possibility that some offerings may be significantly better designed than others cannot be overlooked.

Another issue complicating the literature is the COVID-19 pandemic; articles published prior to the pandemic were examining student outcomes in a much different social, economic, and political context than the one in which we find ourselves at the time of this writing in 2023. The reasons for which students do or don't persist, succeed, and/or graduate due to their pursuit of online coursework may vary today vis à vis in years prior to the pandemic — and at this stage, the data one would need to draw definitive conclusions remains inadequate.

A third issue is the inconsistent use of terms describing online course formats. "Online course" can refer to fully asynchronous courses, but is not infrequently used as well to refer to remote courses with synchronous lectures offered on video-conferencing platforms. Synchronous remote courses often follow conventional face-to-face design and may not reflect the myriad of possibilities enabled by the use of educational technologies in asynchronous settings. Because most of the scholarship we reviewed did not make clear distinctions between these modality subsets, it is likely that we are sometimes comparing apples with, if not precisely oranges, at least markedly different varieties of apples.

Theme 1: Online courses show varying effects on student persistence and success (as reflected by course grades)

The results in this area are mixed. Some scholars find statistically significant differences that point to a negative effect of online course modality on student grades (Goyal et al., 2022; Hart et al., 2016; Xu & Jaggars, 2016; Johnson et al., 2014; Romeo et al., 2021; Wladis et al., 2015; Xu & Jaggars, 2013b). Given the age of the data — meta-analyses of online learning often include results dating back to the 1990s — larger longitudinal studies include courses that wax rudimentary compared with their contemporary iterations. Since it is more or less impossible to assess the quality of design, we cannot assume the incorporation of present-day best practices.

On this subject, Ortagus (2018) pointedly observes that empirical data on course quality are scarce and of limited analytical value given predictable variations in design and delivery, and are thus not necessarily helpful in making determinations about the quality of individual courses.

Some scholars found relationships between course modality and student grades that demonstrate the ostensible equivalency of online and face-to-face courses: both Ni (2018) and Paul and Jefferson (2019), for example, both found no meaningful differences in grade outcomes between online and face-to-face courses.

Finally, there are also a number of studies that show a positive effect of online modalities on course outcomes. For example, Soffer and Nachmais (2018) found not only that online students achieved similar grades as face-to-face students, but that they also reported higher objective levels of engagement with the course, understanding of the course structure, and communication with instructors; indeed, among Soffer and Nachmais's more intriguing results was the observation that students in each modality tend to use and benefit from modality-specific tools. This suggests that trying to make blanket, uncomplicated comparisons of modalities may not be the most accurate way to understand how students approach each one. In a meta-analysis, Means et al. (2013) found essentially no differences in outcomes between purely face-to-face courses and purely online courses, but significantly superior outcomes over *both* online and F2F courses for students in blended (hybrid) modalities. Furthermore, intra-course and intra-institutional outcomes depend to a large degree on the students taking them; as Spencer and Temple (2021) and Wladis et al. (2014) explain, demographic characteristics represent a critical layer of analysis in understanding which kinds of students see the greatest benefit at the level of grades from their participation in online courses. These studies highlight the importance of ruling out the possibility that positive outcomes for a particular modality are driven by demographic groups that are already likely to be performing better than their less-advantaged peers.

Theme 2: The literature demonstrates a positive effect of online courses on transfer and progression to graduation in majors/programs that are taught partially, but not solely, online

The second prominent theme concerns the effect of participation in online courses on a student's retention, progress toward transfer, and eventual graduation. Here, online courses boast much to recommend themselves — particularly when a student takes some, but not all, of their college courses online. In a study by Fischer et al. (2021) of a university with size and demographics similar to our own, online course completion for major requirements increased the number of students who completed their degrees in four years, particularly within low-income student populations. Indeed, each 1% increase in the number of online courses a student took correlated to a commensurate decrease in their overall time to degree. James et al. (2016) found that taking at least some online courses (regardless of general program modality) seemed to have a significant protective effect on retention and graduation rates. This conclusion is also supported by Means et al. (2013), Nadasen & List (2016), Ortagus (2018), Shea & Bidjerano (2014 and 2016), Sublett (2018), and Wavle and Ozogul (2019). Wavle and Ozogul note, in particular, that even in cases where online course grades tend to be slightly lower, earlier participation in online courses leads to higher rates of degree attainment. They identify a "tipping point" of about 40%; i.e., when more than 40% of the classes students enroll in are online, the level of saturation seems to counteract the overall benefit of online courses for degree completion. Only one of the studies we reviewed that addressed the effect of online coursework on retention and graduation rates found a negative impact on those outcomes (Huntington-Klein et al., 2015).

Theme 3: Beyond equity gaps: non-race-based student characteristics as predictors of success in online courses

Our third theme concerns the effect of student characteristics on persistence, success, and degree completion. When discussed, student characteristics are mostly referenced in relation to race-based equity gaps. Equity gaps are indisputably an entrenched problem that must be addressed (Dittmann & Stephens, 2017; Kaupp, 2012; Jaggars, 2011). Yet, online courses may also confer substantial *benefits* on students from demographic groups that are not historically incorporated into conventional equity frameworks — in particular, non-traditional-age students, student parents, and, in some cases, women-identified students.

One often ignored characteristic is the level of previous online experience individual students bring to their online coursework. Bloemer et al. (2018) and James et al. (2016) both found that students who have taken online courses before tend to perform better in subsequent online courses, suggesting that the study and learning skills that advantage students in traditional classroom settings have correlates with online learning. We might conclude from this research that existing performance gaps could be effectively intervened upon by teaching students specific strategies for approaching online courses, in much the same way that efforts are made to communicate effective learning strategies for students in face-to-face settings. The findings of Hachey et al. (2014) — namely, that a student's previous success in an earlier online course is the biggest predictor of their success in future online courses — similarly bolster the notion that effective learning in online settings is itself a discrete skill from which students can benefit if they are presented with opportunities to cultivate it.

After controlling for student characteristics, Wladis et al. (2014) found that differences in course outcomes were no longer significant, suggesting that performance in higher- vs. lower-risk STEM courses seemed to be driven by the background characteristics of the students who choose to enroll in particular courses, rather than the online format of the courses themselves. Xu and Jaggers (2014) also noted improved online performance gaps for women-identified students, older students, and students with lower GPAs. Of note, older students were more likely to persist in online courses and less likely to do so in face-to-face courses, while students with higher GPAs were both more likely to persist and more likely to achieve higher course grades. This is supported by Spencer and Temple (2021), whose research revealed that older students were more likely to pass online courses, while younger students were more likely to pass face-to-face courses. As with Bloemer et al. (2018) and James et al. (2016) above, Xu and Jagger's research leads them to conclude that students who have the background knowledge and experience to succeed in online courses are also more likely to persist and excel in them. Here, we might posit a potential intersection between success and access to education: older students who struggle with the logistical challenges of face-to-face learning may achieve better results in online modalities — not only because they are better equipped to navigate the particularities of the format, but also because their complex lives make it difficult or impossible to negotiate family responsibilities and/or full-time employment without the flexibility that online classes offer. In short: in addition to producing better outcomes, the availability of online courses enables certain categories of students to pursue higher education where it would otherwise not be an option.

Theme 4: Design and context matter to course efficacy

Our final theme concerns the effects of course design and learning context on overall course efficacy. Evidence for pandemic-related gaps is increasingly showing up in the literature; one straightforward example is Goyal et al. (2022), in which the authors compared student grade results from an online Chemistry course in Summer 2020 to the cumulative results of the same course offered face to face in multiple terms between 2017 and 2019. The issue of small sample size aside, this is a case where context is clearly of high relevance, as the exigencies of pandemic-era learning make it all but impossible to control for factors associated with the historical moment rather than course design or student characteristics. The challenges of accounting for these peculiarities are no small part of what motivated our own research strategy of a larger sample size, inclusive of 18 course sequences before, across, and beyond the COVID-19 pandemic.

This is the thematic area in which we also address the difficult-to-measure variable of course design. As with face-to-face courses, pedagogical practices are an important factor in student outcomes. Furthermore, face-to-face courses are rarely subjected to the sort of pedagogical scrutiny under which online courses labor; on the contrary, they are assumed *a priori* to be a superior form of learning on the basis of modality alone. In their meta-analysis of studies of online course efficacy from 1996 to 2008, Means et al. (2013) found that the pedagogical approach modulated the size of online learning effect, although the nature of the relationship is unclear since few details are provided on the specifics of pedagogical approaches. Soffer and Nachmais (2018) likewise concluded that design has a significant impact on outcomes. Our data set examines high-level outcomes across offerings that are comparatively diverse in both pedagogical approach and socio-historical context.

Research Questions

Our aim was to replicate an earlier unpublished institutional study on the efficacy of online STEM courses on a larger set of courses across a wider array of divisions. We sought to determine how online course participation affects downstream learning outcomes, independent of instructor/course differences, specifically for intentionally designed online courses with involvement from the University's Online Education office and its Teaching Center. Details about select course design elements are included in the Methods section. In addition, the current study aimed to determine whether the learning outcomes of different demographic groups are differentially affected by online course participation.

Predictions

We expected to see evidence of pre-existing institutional equity gaps in our data — i.e., worse outcomes independent of modality for minoritized (first-generation and underrepresented) groups. In accordance with independent evidence of women performing better in college courses than men (Voyer and Voyer, 2014), we expected to find evidence of this in our data as well.

Regarding course modality, we sought to determine whether online modalities have a positive or negative downstream effect overall, but also if they differentially affect demographic groups. If the flexibility of online courses improves outcomes for underrepresented groups in particular, we expect to see that equity gaps (lower outcomes) for Underrepresented Groups (URG) and First-Generation (FG) groups are closed in online modalities, whether hybrid or full distance learning. This would suggest that online courses allow minoritized groups opportunities to better self-regulate course participation and learning, providing evidence for benefits in the short term and at the level of specific courses. If online courses generally lead to worse learning, we expect to see that difference exacerbated for underrepresented groups; in this case, we should expect FG and URG outcomes to be worse in online modalities, whether hybrid or full distance learning. We did not have specific predictions about how course modality may differentially affect outcomes by gender.

Methods

The data come from a public California research university which is a designated Hispanic-Serving Institution (27% of students) and Asian American, Native American, Pacific Islander-Serving Institution (30% of students), and whose student population consists of roughly 35% first-generation students. Anonymized student outcome data from 17,042 students for 18 upstream-downstream course sequences from Fall 2019 to Fall 2022 (13 quarters) was provided by the university's institutional research unit, an office responsible for collecting and analyzing statistical data on students, faculty, and staff. Upstream courses were defined as prerequisites for completing some later required or elective major course; downstream courses were defined as those subsequent courses for which enrollment required completing the upstream course with a passing grade. Prior to our receiving or analyzing the data, student IDs were mapped to random identifiers; additionally, we report data in the aggregate here (i.e., at the course level, anonymized via codes assigned to courses within the same division) in order to maintain the anonymity of students and instructors, and we do not report course data with cell sizes containing fewer than 10 students. The distribution of sequences spanned a range of non-STEM disciplines across Arts, Humanities, and Social Sciences. An earlier, unpublished, internal study focused on upstream-downstream sequences with Math prerequisites and Physical/Biological Science, Math, and Computer Science postrequisites; that study found that performance in the downstream courses was generally comparable for students taking the upstream courses either face to face or online, with only one sequence showing a statistically significant difference in downstream performance by upstream modality, and in that case the students taking the upstream course online performed better in the downstream course than the students taking the upstream course face to face.

Course outcome data included letter grades and final grade point scores (numerical versions of letter grades for each student, reported as averages over students and referred to as GPAs throughout) for each student by course offering; only final grade point scores are analyzed in the results section. We chose to analyze grade point scores rather than failure (DFW) rates, because we were interested in assessing the impact of online courses on student *learning* outcomes. In addition, the dataset included the following student demographic information: first-generation status (first generation vs. continuing generation), racial/ethnic status (underrepresented group (URG) vs. non-URG), and gender[1] (men, women). While the dataset also contained more granular categories for racial/ethnic groups, this information was not included in the analyses reported below due to the cell size restriction. Rather, we sought to understand whether upstream modality had an effect on downstream performance for underrepresented student groups (compared to non-underrepresented groups) more broadly.

Recall that our overarching research aim was to determine what impact, if any, upstream course modality has on downstream student outcomes. For the purposes of the current study, "student outcomes" were operationalized via final GPA in each course. Crucially, addressing the present research question required focusing our investigation on course sequences for which there was at least one fully online/distance (O) or hybrid (H) offering of the upstream course, as well as face-to-face (F2F) baseline offering(s) against which to compare outcomes in the online modalities. We define fully online/distance (O) courses as those in which all instruction, whether synchronous or asynchronous, takes place in a distance format. Hybrid (H) courses are those in which some instruction (50% or more) takes place in person and some instruction takes place online.

Data were subsetted to those students who successfully completed the prerequisite (i.e., upstream) course and also participated in the corresponding, subsequent (downstream) courses (rather than students who only completed the upstream, or students who completed the upstream elsewhere — not at the institution under investigation — but completed the downstream at the institution). If students repeated the upstream course multiple times, only their GPA for the final iteration was included in the analysis; similarly, if there were multiple repetitions of the downstream course, only the initial iteration was included. The reasoning behind this was to limit our investigation to understanding how, given successful completion of the upstream, the final modality and/or outcome of the upstream may affect the first attempt at completing the downstream course. Thus, whether O vs. F2F modalities of the upstream led to more repetitions due to failing (DFW) grades was not a question addressed by the current study. Similarly, within-upstream GPA differences by modality are not reported in the following section[2],

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[1] The dataset also included "non-binary" and "unknown" categories, but due to very small numbers of students in each group, this data was not analyzed.

[2] However, note that a preliminary analysis of the data suggests that overall, where there were significant differences between student outcomes based on modality within the upstream course, online outcomes were greater than face-to-face outcomes in the majority of cases (8/10 of the sequences for which differences were significant, at the conventional alpha-level of less than or equal to 0.05). As mentioned above, this conclusion should be interpreted with caution.

as the dataset contained only single offerings for some course sequences, which hindered our ability to disentangle modality from the idiosyncrasies of particular course offerings.

To determine the effect of upstream modality on downstream performance, we fit linear mixed-effects models for each course sequence using the `lme4` package (Bates et al., 2009) in R (R Core Team, 2022), analyzing downstream GPA with upstream modality as a predictor, with random intercepts and random slopes for course term. This structure allows the model to control for variation across instructors and course offerings from quarter to quarter so that the results are not unduly impacted by different instructors having different class average grades. The maximal random-effects structure that allowed the model to converge was used (Barr et al., 2013). The Upstream Modality factor was treatment-coded, as in Appendix A Table A2.

In addition, we were interested in how demographic status and upstream course modality may interact with respect to downstream course grades. Specifically, we sought to determine whether existing equity gaps between under- and overrepresented groups would be either corrected or exacerbated by the different course modalities. As such, we fit separate linear mixed-effects models to investigate the interaction between Modality (Face-to-Face, Hybrid, Online) and FG Status (FG, Non-FG), URG Status (URG, Non-URG), and Gender (M, W), respectively. For these models, factors were deviation-coded; model syntax and contrast-coding schemes are reported in Table A2.

Results

Effect of Upstream Modality

We first report the results of the analyses that took only upstream modality into account (not demographic variables). An overview of the findings is reported in Table 1. In the majority of cases (13 of 18 courses), the results revealed no significant differences in downstream course outcomes based on upstream course modality, suggesting that course modality generally does not have significant long-term impacts on later course outcomes. Model results are reported in Table 3; the following discussion focuses only on those 5 of 18 cases in which linear mixed-effects models (LMEMs) did reveal significant differences. The number of observations per course per modality is given for all courses in Appendix A, and full model results are available in Table B1 of Appendix B.

# of course sequences	**Summary of results**
13/18	No significant differences in downstream outcomes by upstream modality
4/18	Online/hybrid outcomes were significantly better than in-person

	ones
1/18	In-person outcomes were significantly better than online/hybrid ones

Table 1. Overview of findings in terms of statistical differences in downstream outcomes on the basis of upstream modality.

As indicated in Table 1, the vast majority (13 of 18, or 72%) of sequences analyzed revealed no differences in downstream GPA on the basis of upstream course modality. This provides strong evidence in favor of the conclusion that online course modalities do not lead to worse learning downstream compared to in-person modalities. Representative model results for five of these thirteen sequences are reported in Table 2. The remainder of the model results can be found in Table B1 of Appendix B.

Course Sequence	**Mean GPA**		**Upstream Modality**	
	F2F	**O**	**t-value**	**p-value**
A2 → A3	2.8	2.8	0.09	0.9
B1 → B2	3.3	3.7	1.2	0.3
C1 → C2	3.3	3.1	-0.7	0.5
D1 → D2	3.4	3.3	0.4	0.7
H1 → H4	2.9	3.0	1.2	0.2

Table 2. LMEM results for five of the thirteen course sequences where there were non-significant differences by upstream modality. A positive t-value means that average grades in the downstream course were higher for students who took the upstream course online, but in these cases the differences were not statistically significant. See Appendix B for results of all models.

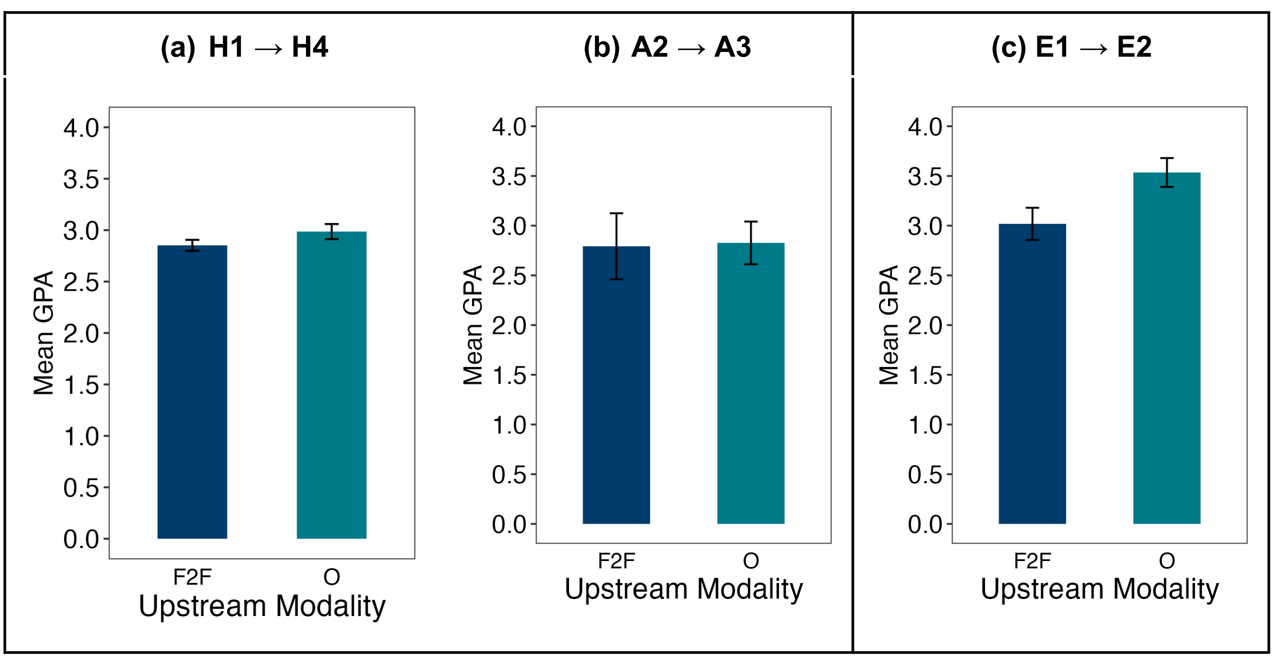
Only five of the eighteen course sequences analyzed revealed significant differences in downstream performance on the basis of upstream modality. The model results for these sequences are reported in Table 3 below.

Course Sequence	**Mean GPA**			**Summary of Results**	**Upstream Modality**	
	F2F	**O**	**H**		**t-value**	**p-value**
E1 → E2	3.0	3.5	–	O > F2F	**2.2**	***0.04**
F1 → F2	2.9	2.5	2.2	F2F ≈ O	-0.9	0.4
				F2F > H	**-2.2**	***0.03**
H1 → H2	3.0	3.1	2.9	O > F2F	**3.6**	*****0.0004**
				F2F ≈ H	1.5	0.13
H1 → H3	2.9	3.0	2.6	O > F2F	**2.0**	***0.05**
				F2F ≈ H	-1.4	0.2

D3 → D4	3.1	3.1	3.4	F2F ≈ O	1.5	0.1
				H > F2F	**3.5**	******0.0005***

Table 3. LMEM results for selected course sequences, where there were significant differences by upstream modality. See Appendix 3 for results of all models.

The summary of course sequences that revealed significant differences is as follows. For E1 → E2, results revealed significantly better outcomes following online completion of the upstream course (mean GPA of 3.5) compared to in-person completion of the upstream (mean GPA = 3.0). For F1 → F2, course outcomes were significantly higher following in-person completion of the upstream (mean GPA = 2.9) than hybrid completion of the upstream (mean GPA = 2.2). GPA for in-person upstreamers was also numerically higher than GPA for online completion (mean GPA = 2.5), but this difference did not reach significance. For H1 → H2, results revealed significantly better outcomes following online completion of the upstream (mean GPA = 3.1) compared to in-person completion (mean GPA = 3.0). Though the numerical difference between the means was small (~0.1 grade point), after taking into account the different average grades across different offerings of the downstream course, the average difference due to upstream modality was significant. There was no significant difference between in-person and hybrid (mean GPA = 2.9) completion of the upstream. For H1 → H3, downstream GPA was significantly higher following online completion of the upstream (mean GPA = 3.0) compared to in-person completion (mean GPA = 2.9), though again, the numerical difference was only ~0.1 grade point. Though the GPA of hybrid upstreamers (mean GPA = 2.6) was numerically lower than that of in-person upstreamers, this difference did not reach significance. D3 → D4 showed significant differences by modality. Here, downstream GPA was significantly higher following hybrid completion of the upstream (mean GPA = 3.4) compared to in-person completion of the upstream (mean GPA = 3.1). There was no difference in downstream GPAs for in-person versus online completion of the upstream (mean GPA was 3.1 for both). Representative plots are included in Figure 1.



(a)/(b) No significant differences in downstream outcomes by upstream modality.	(c) In-person upstream leads to worse downstream outcomes.

Figure 1. Representative plots of downstream average grade point scores by upstream modality for H1 → 4, A2 → 3, and E1 → 2. Only the E1 → 2 sequence reveals a significant difference in outcomes by modality, such that online upstreamers perform better in the downstream.
F2F = face-to-face; **O** = online

Taken together, the results suggest that in most cases, upstream modality is not a significant predictor of downstream GPA. The cases where there are significant differences tentatively suggest that outcomes are generally better following online iterations (i.e., either fully online or hybrid) of the upstream compared to in-person ones. There was one exception to this (F1 → F2), where in-person upstream completion resulted in better downstream outcomes, but this was only true for the in-person vs. hybrid comparison. Finally, it should be noted that even where there were significantly better outcomes for one modality vs. the other, these differences tended to be small in terms of grade points; only the difference in upstream modality for E1 led to a difference of means large enough to affect letter grade in the downstream; this finding is consistent with previous investigations of course outcomes by modality within single courses (Soffer & Nachmais, 2018; Wavle & Ozogul, 2019; i.a.), as opposed to course sequences.

Equity Analyses

Separate LMEMs were fit to each of the following demographic variables for each course sequence. Models tested the interaction between Upstream Modality and the following demographic variables: (i) First-Generation Status, (ii) Underrepresented Racial/Ethnic Group (URG) Status, and (iii) Gender, the results of each of which are reported in the relevant subsections below.

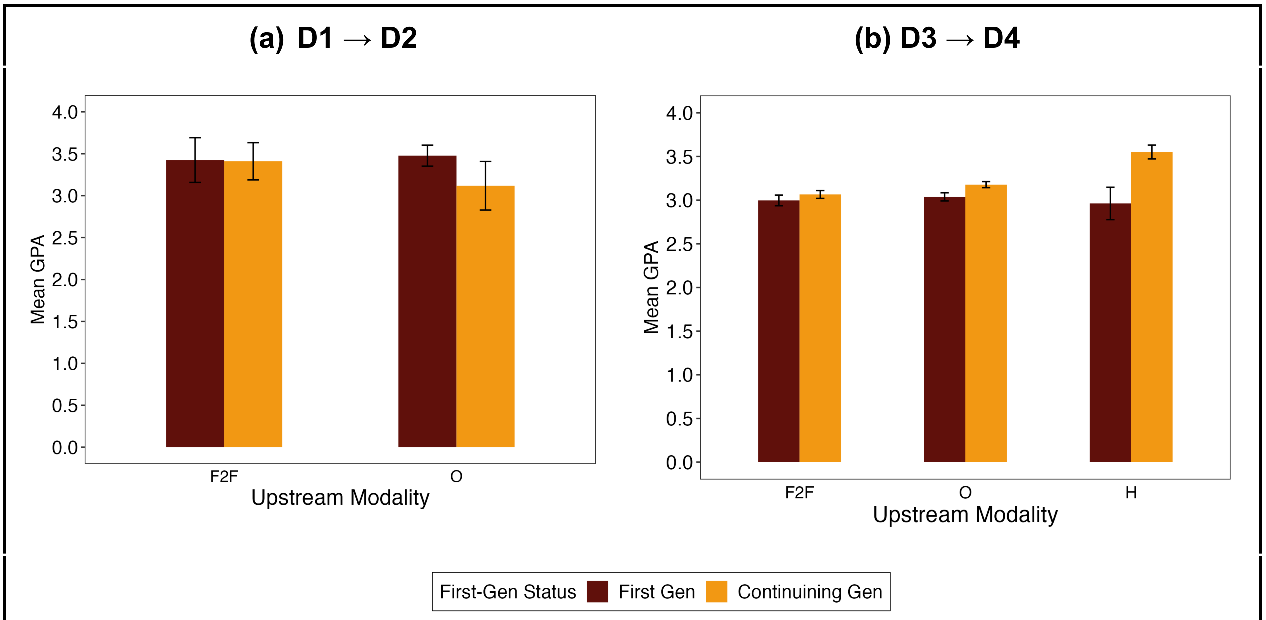
Effect of First-Generation Status

The results for courses with significant main effects of URG status or a significant Modality x URG Status are reported in Table 4. 14 of 18 course sequences showed no significant main effect of FirstGen status and no significant interaction between FirstGen Status and Upstream Modality; results of the LMEMs for these course sequences are reported in Table B2 of Appendix B. For two of the remaining course sequences (A2 → A3 and D3 → D4), FirstGen GPA was significantly lower than that of Continuing-Generation (CG) students. This accords with previous investigations on FirstGen equity gaps (Dittmann & Stephens, 2017) as well as existing institutional data. In addition, one course sequence (H1 → H2) revealed marginally worse outcomes for FG compared to CG students. Surprisingly, one course sequence (D1 → D2) revealed significantly better outcomes for FG students (plotted in Figure 2a). Though there appears to be a trend towards worse outcomes for CG students only within the online upstream group, the interaction between modality and FG status does not reach significance. We suggest that this may be due to the fact that D1 is a class for non-native English speakers, containing a large number of international students. We return to a more thorough discussion of this point in the Discussion. One course sequence (D3 → D4) revealed a significant interaction between FirstGen status and Upstream Modality (Figure 2b). The in-person v. online contrast resulted in a marginal interaction such that CG GPA was marginally higher in online offerings (mean GPA = 3.2) compared to in-person offerings (mean GPA = 3.0); in contrast, FirstGen GPA remained stable, and lower (mean GPA = 3.0), across both modalities. Similarly, the in-person v. hybrid contrast resulted in a significant interaction such that CG GPA was higher in online offerings (mean GPA = 3.5) compared to in-person offerings. Meanwhile, FirstGen GPA once again remained stable but low (mean GPA = 3.0) across modalities.

This one sequence where CG GPA is boosted relative to FirstGen GPA in online modalities is suggestive of the development of an equity gap in online offerings that is not evident in the in-person offerings. This potentially implicates a need to revisit the design of the online offerings of this course sequence in order to determine the cause of this undesirable and somewhat unexpected pattern, especially given that online modalities typically tend to improve accessibility for FirstGen/URG students. As discussed in §2, however, this generalization does not always straightforwardly lead to equal or improved GPA within single courses. Despite this particular data point, the overwhelming majority of course sequences (17 of 18) do not display any evidence of a significant interaction between FirstGen status and Upstream Modality.

Course Sequence	Effect	Modality Comparison	t-value	p-value
H1 to H2	**FG**	**–**	**-1.8**	**0.07**
	FG*Modality	F2F v. O	0.8	0.4
		F2F v. H	-0.6	0.6
A2 to A3	**FG**	**–**	**-3.0**	**0.006**
	FG*Modality	F2F v. O	0.2	0.8
		F2F v. H	–	–
D1 to D2	**FG**	**–**	**1.95**	**0.05**
	FG*Modality	F2F v. O	-0.5	0.6
		F2F v. H	–	–
D3 to D4	FG	–	-0.9	0.4
	FG*Modality	F2F v. O	-0.7	0.5
		F2F v. H	**-2.7**	**0.007**

Table 4. LMEM results for selected course sequences, where there were significant differences by FirstGen status or between FirstGen status and upstream modality. Significant differences are highlighted in green; marginal differences are indicated in yellow. See Table B2 of Appendix B for results of all models.



Downstream outcomes are significantly worse for CG groups, but this appears to primarily be the case in the CG online groups. The interaction between modality and FG status does not reach significance.	Downstream outcomes are significantly better for CG online upstream groups.

Figure 2. FG/CG differences by modality for selected course sequences. Only D3 → 4 reveals a significant interaction between FG status and modality, such that online CG outcomes are better than F2F ones.
F2F = face-to-face; **O** = online

Effect of Underrepresented Racial/Ethnic Group (URG) Status

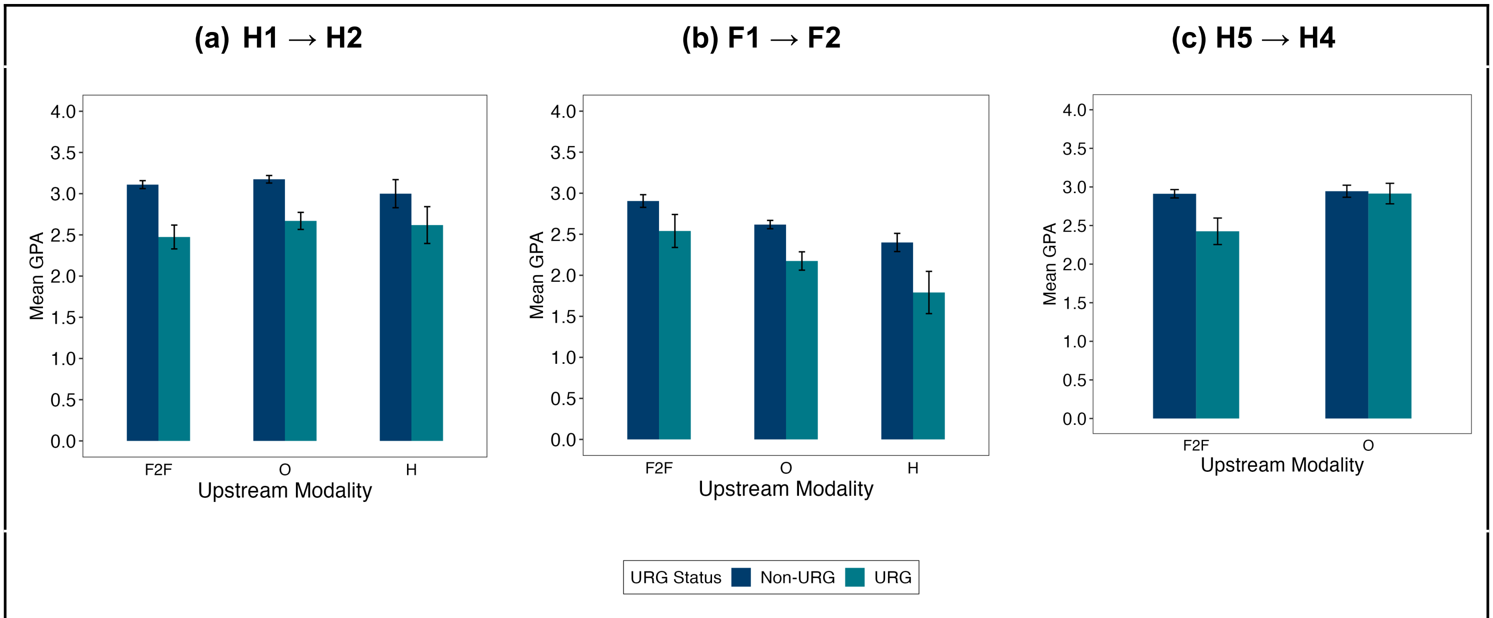
For those courses that revealed significant main effects of URG status or a significant Modality x URG Status, results are reported in Table 5. 10 of 17 course sequences[3] showed no main effect of URG status (i.e., no significant difference between URG and non-URG outcomes, independent of upstream/downstream status); results of the LMEMs for these course sequences are reported in Table B3 of Appendix B. In four of the remaining course sequences (significant differences in H1 → H2, H5 → H4, B1 → B2, and D3 → D4), URG GPA within the downstream course was significantly lower than non-URG GPA. In the remaining three course sequences (F1 → F2, H5 → H3, and A2 → A3), URG GPA in the downstream course was marginally lower than non-URG GPA. Only two course sequences (H5 → H4 and D3 → D4) displayed a significant interaction between URG status and upstream modality. For H5 → H4, URG in-person GPA (mean GPA = 2.4) was significantly lower than non-URG in-person GPA (mean GPA = 2.9), but online outcomes were the same for URG and non-URG students (mean GPA of 2.9 for both). This interaction is plotted in Figure 3c. We interpret this result as an instance of an equity gap present in the in-person offerings (lower URG student outcomes) being closed in the online offerings (equal outcomes for URG and non-URG students). For D3 → D4, the results reveal a crossover interaction: URG GPA (3.2) was higher than non-URG

[3] D1 to D2 was excluded from this analysis, as only non-URG students are enrolled in the downstream course (WRIT 26), a writing course for international students.

GPA (2.99) following face-to-face offerings, but conversely, non-URG GPA (3.1) was higher than URG GPA (3.07) following online offerings. While the difference between URG and non-URG outcomes in the online modality is very small, the boost for URG GPA in face-to-face modality runs counter to the overall institution-wide trend of URG outcomes generally being worse than non-URG ones. This suggests that a closer look at the design of D3 may be warranted.

Course Sequence	Effect	Modality Comparison	t-value	p-value
F1 to F2	**URG**	**–**	**-1.8**	**0.07**
	URG*Modality	F2F v. O	-0.4	0.7
		F2F v. H	-0.8	0.4
H1 to H2	**URG**	**–**	**-5.2**	**2.8e-07**
	URG*Modality	F2F v. O	1.0	0.3
		F2F v. H	0.7	0.5
H5 to H3	**URG**	–	**-1.8**	**0.07**
	URG*Modality	F2F v. O	0.4	0.7
H5 to H4	**URG**	–	**-2.1**	**0.02**
	URG*Modality	**F2F v. O**	**1.96**	**0.05**
		F2F v. H	–	–
A2 to A3	**URG**	–	**-1.9**	**0.07**
	URG*Modality	F2F v. O	1.6	0.1
B1 to B2	**URG**	**–**	**-2.9**	**0.005**
	URG*Modality	F2F v. O	-0.3	0.7
D3 to D4	**URG**	**–**	**2.0**	***0.04**
	URG*Modality	**F2F v. O**	**-2.4**	***0.02**
		F2F v. H	-1.5	0.1

Table 5. LMEM results for selected course sequences, where there were significant differences by URG status or between URG status and upstream modality. Significant differences are highlighted in green; marginal differences are indicated in yellow. See Table B3 of Appendix B for results of all models.



Downstream URG outcomes are significantly worse, but not modulated by upstream modality.	Downstream URG outcomes are marginally worse, but this trend is not modulated by upstream modality.	Downstream outcomes are significantly worse for URG in-person upstream groups.

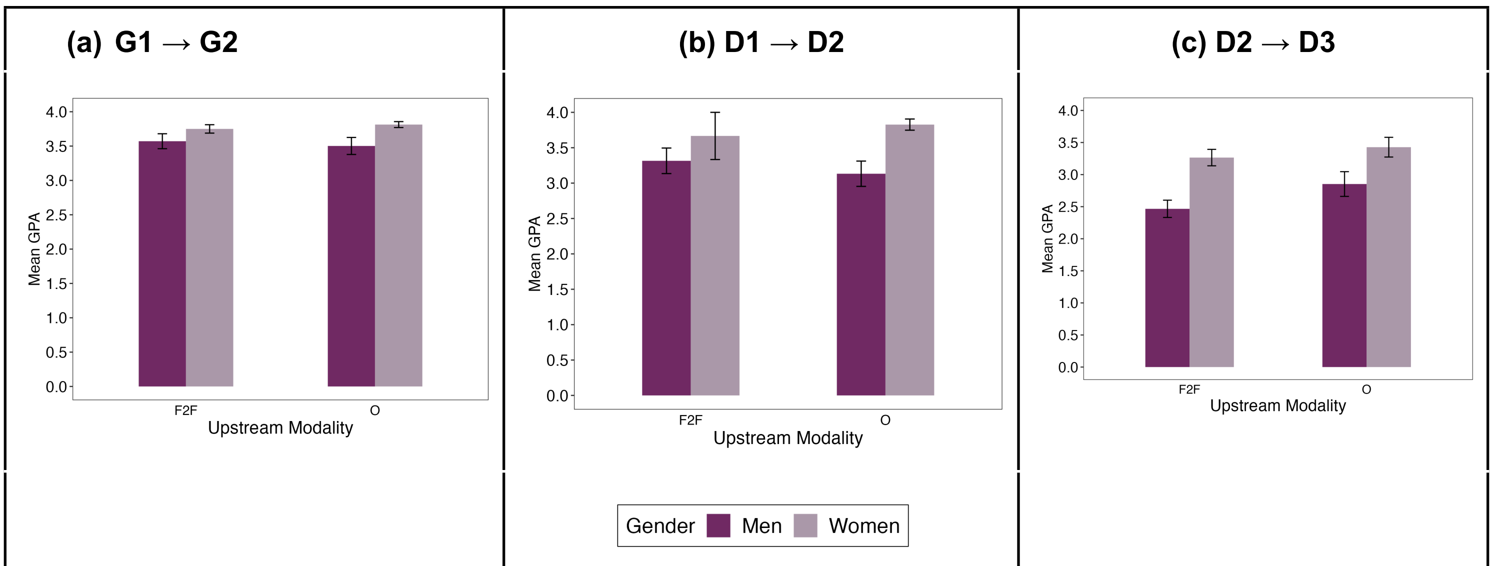
Figure 3. URG/non-URG differences by modality for selected course sequences. Only H5 → 4 reveals a significant interaction between URG status and modality, such that F2F URG outcomes are worse than online ones. **F2F** = face-to-face; **O** = online; **H** = hybrid

Effect of Gender

Models investigating the effect of gender on course outcomes only included data from students who self-identified as men or women; a very small number of students across the course sequences analyzed self-identified as non-binary (or other/unknown), but due to low statistical power, analysis of this data was not possible. Therefore, the models probe the interaction between Upstream Modality, on the one hand, and only Men v. Women on the other. Largely, there were no effects of gender; 14 of 18 course sequences revealed no significant main effect of gender. In three of the remaining course sequences (G1 → G2, D2 → D3, D3 → D4), the GPA of male students was significantly lower than that of female students; model statistics are reported in Table 6. For G1 → G2, the mean downstream male GPA was 3.5, whereas the mean downstream female GPA was 3.8. For D2 → D3, the mean downstream male GPA was 2.6, and the mean downstream female GPA was 3.3. For D3 → D4, the mean downstream male GPA was 3.0, and the mean downstream female GPA was 3.2. In the one remaining course sequence (D1 → D2), the GPA of male students (mean GPA = 3.2) was marginally lower than that of female students (mean GPA = 3.8). In one other course sequence, a small number of students who completed the downstream course with a GPA of 0.0 made it appear as if there was a significant main effect of Gender and a significant interaction of Gender and Upstream Modality. Excluding these data points eliminated these significant effects; as such, we do not report these results. There were no other significant interactions by gender. Full model results can be found in Appendix B, Table B4.

Course Sequence	Effect	Modality Comparison	t-value	p-value
G1 to G2	**Gender**	**–**	**2.7**	****0.008**
	Gender*Modality	F2F v. O	-0.8	0.4
D1 to D2	**Gender**	**–**	**1.9**	**0.06**
	Gender*Modality	F2F v. O	0.8	0.4
D2 to D3	**Gender**	**–**	**3.6**	*****0.0004**
	Gender*Modality	F2F v. O	-0.6	0.6
D3 to D4	**Gender**	**–**	**4.3**	*****1.43e-05**
	Gender*Modality	F2F v. O	-1.5	0.1
		F2F v. H	-0.8	0.4

Table 6. LMEM results for selected course sequences, where there were significant differences by gender or between gender and upstream modality. Significant differences are highlighted in green; marginal differences are indicated in yellow. See Table B4 of Appendix B for results of all models.



Downstream outcomes for men are significantly worse, but not modulated by upstream modality.	Downstream outcomes for men are marginally worse, but this trend is not modulated by upstream modality.	Downstream outcomes are significantly worse for men in in-person upstream groups.

Figure 4. Gender differences by modality for selected course sequences, where men's downstream outcomes are worse than women's, regardless of modality.
F2F = face-to-face; **O** = online

Discussion

The data are, in a word, underwhelming: online prerequisite courses do not negatively impact postrequisite course performance. Indeed, as evidenced by the data, there may even be a slight tendency for online courses to lead to *better* downstream performance than for identical courses taken face-to-face. These results are also largely aligned with national data, which, although mixed, comprise numerous studies finding no difference in outcome between F2F and online courses.

As noted earlier in this paper, the scope and reach of our investigation have been somewhat limited by external factors: namely, the preponderance of pandemic-era courses in our data set. Given the emergent nature of pandemic teaching and the extremely short transitional timeframe allotted to instructors during that historical moment, we hypothesize that the same project repeated several years hence — when instructors will have benefitted from more relaxed production timelines and opportunities to further enhance their course design — will show outcomes commensurate with their efforts and with the post-pandemic era. We look forward to conducting that research down the road.

There are also pieces to the online course puzzle that cannot be adequately addressed with quantitative methods. Some questions that could enhance our understanding of these results would be best explored through a mixed-methods approach that includes a qualitative analysis of learning outcome measures, the reasons why students choose to take online courses in the first place, and students' subjective experiences of their work in online courses. Finally, we cannot make extended claims about the relevance of outcomes outside the context of purpose-designed online courses; while we have demonstrated that well-designed online courses lead to equal outcomes, the same may not hold true for online courses that have not undergone an intentional design process.

The results of this study do not find empirical evidence for differences in postrequisite outcomes between students who participate in face-to-face vs. online prerequisite courses. Though a follow-up mixed-methods study investigating motivations for online course enrollment should ideally be conducted, our institution's enrollment data alone suggest that student demand for online courses continues to increase. Furthermore, we suspect that this is equally true at many other U.S. institutions.

Given the previously documented benefits that online courses bestow on short-term flexibility and long-term outcomes — particularly for students in marginalized groups — we conclude that colleges and universities should, where appropriate, (i) continue to make high-quality, purpose-designed online courses available, and (ii) expand online offerings to further support students' timely and effective progress toward their degrees.

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Appendix A: Methods tables

Course Sequences (Anonymized)	# of Observations by Modality					
	Upstream			Downstream		
	F2F	O	H	F2F	O	H
A1 to A2	11	25	–	*	18	12
A2 to A3	14	15	*	*	29	–
B1 to B2	29	22	–	39	12	–
C1 to C2	21	21	–	10	–	32
C1 to C3	37	40	*	37	42	–
D1 to D2	39	57	–	38	48	10
D2 to D3	133	95	16	148	75	21
D3 to D4	910	1443	143	642	1788	72
E1 to E2	22	23	*	–	54	–
F1 to F2	207	504	82	144	775	–
F2 to F3	144	775	–	106	232	–
F2 to F4	144	775	–	79	166	–
H1 to H2	1373	1699	314	1113	1091	119
H1 to H3	1216	1562	315	979	914	63
H1 to H4	1216	1562	315	933	886	61
H5 to H3	385	304	–	169	481	39
H5 to H4	403	205	–	133	431	44
G1 to G2	146	142	–	75	135	78

Table A1. Count of upstream-downstream course sequences per division. *Data not reported due to cell size restriction (n < 10).

Upstream Modality		
	Model	**Contrasts**
	`lmer(avgGradePointScore ~ UpstreamModality + (1 + UpstreamModality | CourseTerm)`	a. `F2F = 0, H = 0, O = 1` b. `F2F = 0, H = 1, O = 0`
Upstream Modality by Demographic Group		

Demographic Groups	Model	Contrasts
Continuing Generation vs. First Generation	`lmer(avgGradePointScore ~ UpstreamModality * FirstGen + (1 + UpstreamModality | CourseTerm)`	`CG = -1/2, FG = 1/2`
Non-URG vs. URG	`lmer(avgGradePointScore ~ UpstreamModality * URG + (1 + UpstreamModality | CourseTerm)`	`Non-URG = -1/2, URG = 1/2`
Men vs. Women	`lmer(avgGradePointScore ~ UpstreamModality * Gender + (1 + UpstreamModality | CourseTerm)`	`M = -1/2, W = 1/2`

Table A2. Model syntax and contrast coding schemes for linear mixed-effects models (`lme4`).

Appendix B: Model results

Upstream Modality

Course Sequence	Mean GPA			Summary of Results	Upstream Modality	
	F2F	O	H		t-value	p-value
E1 → E2	3.0	3.5	–	**O > F2F**	**2.2**	***0.04**
F1 → F2	2.9	2.5	2.2	F2F ≈ O	-0.9	0.4
				F2F > H	**-2.2**	***0.03**
F2 → F3	3.7	3.7	–	F2F ≈ O	0.3	0.8
F2 → F4	3.1	3.2	–	F2F ≈ O	0.2	0.8
H1 → H2	3.0	3.1	2.9	**O > F2F**	**3.6**	*****0.0004**
				F2F ≈ H	1.5	0.13
H1 → H3	2.9	3.0	2.6	**O > F2F**	**2.0**	***0.05**
				F2F ≈ H	-1.4	0.2
H1 → H4	2.9	3.0	–	F2F ≈ O	1.2	0.2
H5 → H3	2.9	2.9	–	F2F ≈ O	0.2	0.9
H5 → H4	2.8	2.9	–	F2F ≈ O	0.9	0.4
G1 → G2	3.7	3.7	–	F2F ≈ O	-0.09	0.9
C1 → C2	3.4	2.9	–	F2F ≈ O	-1.4	0.2
C1 → C3	3.3	3.1	–	F2F ≈ O	-0.7	0.5
A1 → A2	2.9	2.5		F2F ≈ O	-0.8	0.4
A2 → A3	2.8	2.8	–	F2F ≈ O	0.09	0.932
B1 → B2	3.3	3.7	–	F2F ≈ O	1.2	0.3
D1 → D2	3.1	3.1	3.4	F2F ≈ O	1.5	0.1
				H > F2F	**3.5**	*****0.0005**
D2 → D3	2.7	3.0	–	F2F ≈ O	0.8	0.5
D3 → D4	3.0	3.1	3.4	F2F ≈ O	1.5	0.1
				H > F2F	**3.6**	*****0.0005**

Table B1. Model results for downstream outcomes by upstream modality analysis.

First-Generation Status

Course Sequence	Effect	Modality Comparison	t-value	p-value
E1 → E2	FG	–	-0.9	0.4
	FG*Modality	F2F v. O	-0.5	0.6
F1 → F2	FG	–	-0.4	0.7
	FG*Modality	F2F v. O	-0.3	0.8
		F2F v. H	-0.008	0.99
F2 → F3	FG	–	1.3	0.2
	FG*Modality	F2F v. O	-0.7	0.5
F2 → F4	FG	–	-0.8	0.4
	FG*Modality	F2F v. O	-0.7	0.5
H1 → H2	**FG**	**–**	**-1.8**	**0.07**
	FG*Modality	F2F v. O	0.8	0.4
		F2F v. H	-0.6	0.6
H1 → H3	FG	–	-0.2	0.8
	FG*Modality	F2F v. O	-0.7	0.5
		F2F v. H	-0.3	0.7
H1 → H4	FG	–	0.07	0.9
	FG*Modality	F2F v. O	0.8	0.4
H5 → H3	FG	–	-1.5	0.1
	FG*Modality	F2F v. O	-0.04	0.97
H5 → H4	FG	–	-0.9	0.4
	FG*Modality	F2F v. O	0.9	0.4
G1 → G2	FG	–	-0.09	0.9
	FG*Modality	F2F v. O	-0.04	0.97
C1 → C2	FG	–	0.03	0.98
	FG*Modality	F2F v. O	-0.6	0.5
C1 → C3	FG	–	-1.1	0.3
	FG*Modality	F2F v. O	0.8	0.43
A1 → A2	FG	–	0.07	0.9
	FG*Modality	F2F v. O	-0.7	0.5
A2 → A3	**FG**	**–**	**-3.0**	****0.006**
	FG*Modality	F2F v. O	0.2	0.8
B1 → B2	**FG**	**–**	**-1.8**	**0.08**
	FG*Modality	F2F v. O	-0.3	0.8
D1 → D2	**FG**	**–**	**1.95**	***0.05**

	FG*Modality	F2F v. O	-0.5	0.6
D2 → D3	FG	–	0.5	0.6
	FG*Modality	F2F v. O	0.4	0.7
D3 → D4	FG	–	-0.9	0.4
	FG*Modality	F2F v. O	-0.7	0.5
		F2F v. H	**-2.7**	****0.007**

Table B2. LMEM results for first-generation status and modality. Significant differences are highlighted in green; marginal differences are indicated in yellow.

URG Status

Course Sequence	Effect	Modality Comparison	t-value	p-value
E1 → E2	URG	–	0.5	0.6
	URG*Modality	F2F v. O	-1.4	0.2
F1 to F2	**URG**	**–**	**-1.8**	**0.07**
	URG*Modality	F2F v. O	-0.4	0.7
		F2F v. H	-0.8	0.4
F2 → F3	URG	–	0.6	0.5
	URG*Modality	F2F v. O	-0.8	0.4
F2 → F4	URG	–	-0.7	0.5
	URG*Modality	F2F v. O	-1.4	0.2
H1 → H2	**URG**	**–**	**-5.2**	*****2.8e-07**
	URG*Modality	F2F v. O	1.0	0.3
		F2F v. H	0.7	0.5
H1 → H3	URG	–	-0.5	0.6
	URG*Modality	F2F v. O	-1.1	0.3
		F2F v. H	0.09	0.9
H1 → H4	URG	–	-1.2	0.2
	URG*Modality	F2F v. O	1.1	0.3
H5 → H3	**URG**	–	**-1.8**	**0.07**
	URG*Modality	F2F v. O	0.4	0.7
H5 → H4	**URG**	–	**-2.1**	***0.02**
	URG*Modality	**F2F v. O**	**1.96**	***0.05**
G1 → G2	URG	–	1.1	0.3
	URG*Modality	F2F v. O	1.4	0.2
C1 → C2	URG	–	-0.2	0.9
	URG*Modality	F2F v. O	-0.7	0.5
C1 → C3	URG	–	0.5	0.6
	URG*Modality	F2F v. O	-0.8	0.4

A1 → A2	URG	–	-0.6	0.5
	URG*Modality	F2F v. O	-0.5	0.6
A2 → A3	**URG**	**–**	**-1.9**	**0.07**
	URG*Modality	F2F v. O	1.6	0.1
B1 → B2	**URG**	**–**	**-2.9**	****0.005**
	URG*Modality	F2F v. O	-0.3	0.7
D1 → D2	URG	–	0.3	0.6
	URG*Modality	F2F v. O*	–	–
D2 → D3	URG	–	0.7	0.5
	URG*Modality	F2F v. O	-0.1	0.9
D3 → D4	**URG**	**–**	**2.0**	***0.04**
	URG*Modality	**F2F v. O**	**-2.4**	***0.02**
		F2F v. H	-1.5	0.1
* No face-to-face URG students in D1 → D2				

Table B3. LMEM results for under-represented status and modality. Significant differences are highlighted in green; marginal differences are indicated in yellow.

Gender

Course Sequence	Effect	Modality Comparison	t-value	p-value
E1 → E2	Gender	–	1.1	0.3
	Gender*Modality	F2F v. O	0.6	0.6
F1 → F2	Gender	–	0.7	0.5
	Gender*Modality	F2F v. O	-0.6	0.6
		F2F v. H	-0.7	0.5
F2 → F3	Gender	–	0.3	0.8
	Gender*Modality	F2F v. O	0.8	0.4
F2 → F4	Gender	–	1.5	0.1
	Gender*Modality	F2F v. O	0.3	0.8
		F2F v. H	–	–
H1 → H3	Gender	–	-0.3	0.8
	Gender*Modality	F2F v. O	0.3	0.8
		F2F v. H	0.02	0.98
H1 → H4	Gender	–	0.6	0.5
	Gender*Modality	F2F v. O	-0.9	0.4
		F2F v. H	–	–
H5 → H3	Gender	–	-0.7	0.5
	Gender*Modality	F2F v. O	-1.3	0.2
		F2F v. H	–	–

H5 → H4	Gender	–	1.3	0.2
	Gender*Modality	F2F v. O	0.2	0.9
		F2F v. H	–	–
G1 to G2	**Gender**	**–**	**2.9**	****0.003**
	Gender*Modality	F2F v. O	0.8	0.4
		F2F v. H	–	–
C1 → C2	Gender	–	1.5	0.2
	Gender*Modality	F2F v. O	-1.2	0.3
		F2F v. H	–	–
C1 → C3	Gender	–	0.008	0.99
	Gender*Modality	F2F v. O	-0.5	0.7
A1 → A2	Gender	–	1.1	0.3
	Gender*Modality	F2F v. O	-0.3	0.8
A2 → A3	Gender	–	0.5	0.6
	Gender*Modality	F2F v. O	-0.9	0.4
B1 → B2	Gender	–	-0.04	0.97
	Gender*Modality	F2F v. O	0.4	0.7
D1 → D2	**Gender**	**–**	**1.96**	***0.05**
	Gender*Modality	F2F v. O	0.8	0.4
		F2F v. H	–	–
D2 → D3	**Gender**	**–**	**3.6**	*****0.0004**
	Gender*Modality	F2F v. O	-0.6	0.6
D3 → D4	**Gender**	**–**	**4.3**	*****1.43e-05**
	Gender*Modality	F2F v. O	-1.5	0.1
		F2F v. H	-0.8	0.4

Table B4. LMEM results for gender and modality. Significant differences are highlighted in green; marginal differences are indicated in yellow.