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Educational disparities in STEM during COVID-induced distance learning and a potential strategy to address them

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Abstract

The COVID-19 pandemic prompted widespread school closures and a swift transition to distance learning, raising concerns about consequences for student success. This study explores academic outcomes in STEM (Science, Technology, Engineering, and Mathematics) courses during COVID-induced distance learning using student-course records at an U.S. public university. We particularly focus on students from underserved populations and who have below average academic outcomes. Employing an expected shortfall regression strategy, we examine outcomes in the bottom quintile and compare differences between students whose household income were in the lowest bracket or without a parent holding a four-year college degree and peers for whom this was not the case, in distance and in-person learning. We show that during distance learning, students in disadvantaged populations in the lowest quintile had average grade differences of 0.11 and 0.06 points, respectively. We also find that targeted instructional changes in an introductory physics course were associated with narrower achievement gaps. These results suggest that while distance learning posed challenges for underserved students, deliberate strategies to increase interaction may potentially support greater equity in STEM education.

1 Introduction

The COVID-19 pandemic significantly disrupted the education system and led to mass school closures worldwide [1]. The majority of colleges and universities transitioned to online/distance learning—84% of all undergraduates in the US had some or all of their classes moved to online-only in Spring 2020 [2]. Distance learning continued for several semesters following the onset of COVID-19. In Fall 2021, 61% of all undergraduate students were enrolled in at least one remote course while 28% were enrolled in remote courses exclusively [3]. Prior to the pandemic, there were some studies that explored the benefits and limitations of online learning. For example, one characteristic of online learning is the flexibility to study at one's own pace [4]. However, this suggests that student success may depend on high self-discipline and time management skills [5]. In addition, the design of a course will also need to be suitable for online learning—the nature and extent of peer and student-faculty interactions must be adapted to ensure student learning outcomes in online courses [6].

Student populations such as Black, Latin, Indigenous students, low-income (household income in the lowest bracket) or first-generation (parents did not complete a four-year college degree) are historically underrepresented in higher education and face barriers to opportunity and high-quality instruction [7]. Promoting equity in higher education is a major priority in the United States [8], and with the increase of online learning in higher education, equity in online learning should be explored. Investigating the effect of distance learning on disadvantaged students is crucial to address the extent of gaps in education.

We focus primarily on students who are low-income (household income in the lowest bracket) or first-generation (parental education less than a four-year college degree), who face great challenges in higher education [9]. Students who are low-income or first-generation disproportionately come from ethnic and racial minority backgrounds, have less academic preparation, tend to be older, and face more obligations outside college. Even after taking their background, preparation, and enrollment characteristics into account, students who are low-income or first-generation still encounter greater risks of failure in higher education [10–16]. They are less likely to participate in student experiences that promote academic success such as studying in groups, interacting with faculty and peers, and utilizing support services [15, 17–26].

Specifically, in distance learning, students whose household income is in the lowest bracket are more likely to face practical challenges such as not having a quiet workplace, not knowing where to seek course assistance, and managing conflicts with home responsibilities [27]. They are also more likely to face internet connectivity issues, hardware and software issues that negatively impact the effectiveness of distance learning [8, 28]. On the other hand, first-generation students may face challenges in distance learning due to staying in households where their parents lack the educational experience to provide support. At the same time, they are more often expected to assist with sibling care at home [29]. Moreover, first-generation students tend to have lower access to digital tools and are less familiar with school culture, knowledge and skills which in turn affect their academic performances [30].

When studying the academic gap, we are particularly interested in gaps among students who have below average academic outcomes. Many studies have investigated strategies to improve the performance of low-performing postsecondary students [31–35]. Students who begin with poor performance tend to struggle throughout their academic journey [33], a problem which may be exacerbated by limited in-person instruction and interaction. Students at the lower end of academic outcomes are at risk of being placed on academic probation, which can delay graduation [36]. First generation students and students from low-income families already face a graduation gap: undergraduates who are both low-income and first-generation have a six-year graduation rate at four-year institutions of 41% compared to 73% for undergraduates who are neither low-income nor first-generation [37]. We hypothesize that lower achieving students may be more negatively affected by distance learning than an average student, further enlarging the achievement gap between students who are low-income or first-generation and their peers. While prior literature suggest that distance learning may have no impact or even improve average student outcomes [38–40], additional evidence suggests online learning may negatively affect low-performing students [41, 42].

In this study, we focus on STEM courses in higher education. Enhancing social mobility for students is important for universities, and STEM is often seen as a vehicle for economic opportunity and social mobility [43]. STEM degrees have long been promoted to students as a potential path to high-paying careers [9, 44–47], and there is a robust and growing demand for students skilled in STEM disciplines in both STEM and non-STEM occupations [48]. Students pursuing STEM majors are more likely to have a job aligned with their field of study compared to those from non-STEM majors [46] and see significant wage advantages in the job market [45, 46]. However, students from underrepresented populations are less likely to study or complete STEM degrees. Once they are enrolled in a STEM program, retaining these students poses a great challenge due to factors such as insufficient pre-college preparation and lack of supportive social environments [49–52]. Students who are first-generation or whose parents have lower incomes are more likely to leave their STEM program by changing majors or leaving college without completing a degree [49, 53]. The effect distance learning may have on the academic performance of students who are low-income and first-generation in STEM courses is of interest, as college GPA and first-semester GPA are important predictors of their STEM degree attainment [54–56] and of obtaining a STEM-related job [57].

Distance learning produces additional challenges when it comes to STEM courses, as many STEM courses rely on specialized software and equipment which may not be readily accessible outside of traditional classroom settings [58]. In distance learning, students in STEM courses report concern about losing hands-on experience in laboratories [59, 60] and struggle with engagement and motivation after the transition [27, 61–63]. The intersection of STEM, barriers to success in STEM faced by students who are low-income and first-generation, and challenges faced in a distance learning setting are thus of great interest.

The primary objective of our study is to examine the association between COVID-induced learning modality (in particular, distance learning) and student academic outcomes and learning gaps in STEM courses, particularly focusing on underrepresented and lower performing students. To achieve this goal, we obtain longitudinal student administrative and educational outcome data from the University of Michigan (referred to as the University hereafter) during the years from Fall 2016 to Fall 2022. Our dataset contains information about student course enrollment and their respective performances, as well as their demographic, socioeconomic and academic backgrounds. Focusing on semester-long undergraduate courses, our data contains over 1.2 million student-course records, more than half of which are for STEM courses. The study has received approval from the University's Institutional Review Board and the data are procured through a Memorandum of Understanding (MOU) agreement with the University's enrollment management office to ensure strict protection of student privacy.

Before the onset of the COVID-19 pandemic, almost all classes at the University were taught in person. In March 2020, the University announced it would switch all classes to distance learning to limit the spread of COVID-19. It then resumed limited in-person classes in Fall 2020 and Winter 2021. However, the majority (75.1% and 89.2%, respectively) of classes were taught online during these terms. Later in Fall 2021, a significant portion (86.3%) of classes returned to in-person learning while some classes (13.7%) continued to be taught online or in a hybrid mode. The selection of learning modality is primarily at the discretion of individual instructors, in alignment with guidelines from the University and their respective academic units. These differential transitions in learning modality by courses thus allow us to compare academic achievements across different student subgroups under different learning modalities, while controlling for the effect of the pandemic itself.

The results indicate that COVID-induced distance learning is linked to larger academic gaps in STEM courses. Students whose household income were in the lowest bracket and first-generation students in the lowest quintile have grade point differences of 0.114 and 0.064 under distance learning, respectively, compared to their peers. This difference is significant given the lower-quintile mean grade points of 2.48 overall, and 2.00, 2.02, and 1.69 for students who are low-income, first-generation, and both low-income and first-generation, respectively.

Moreover, at below a 2.0 cumulative GPA, and for some colleges below a 2.0 semester GPA, students will be placed on academic probation with the risk of having enrollment withheld or being placed on academic recess for one year. In some majors, students who achieve below 2.0 grade points will fail to fulfill the minimum requirement for common required and core courses in their majors. Thus, a reduction of 0.114 or 0.064 in grade points for students within the lowest quintile can result in serious academic consequences and delays to graduation. In non-STEM courses, we see a smaller gap of around 0.05 grade points.

Given the greater disparities observed for lower-performing students, we then investigate potential instructional interventions which may reduce disparities in COVID-induced distance learning. Specifically, we consider an introductory physics course that, in each semester starting from Fall 2019, offered additional sections as part of a recent university initiative, i.e., the Foundational Course Initiative (FCI), aimed at improving learning experiences for students. Course sections offered as part of this programs provide students with greater access to instructor support and more interactions with their peers consistently implemented during the in-person and distance learning environments. For example, during distance learning, these sections continued to offer students greater interactions through discussions and group work facilitated by online platforms such as Zoom and Gather Town.

We find that this course initiative, which provide students with additional support and student-instructor and peer interactions, significantly reduces the observed achievement gaps in COVID-induced distance learning. These findings not only corroborate previous results in the literature that increased interaction with peers and instructors is associated with greater success in online learning in general [6] and in the context of the pandemic [64, 65], they further demonstrate that enhanced interaction can effectively narrow the achievement gaps for students from disadvantaged backgrounds.

2 Results

2.1 Institutional background

We use student administrative and educational outcome data from a large public university in the US which enrolls around fifty thousand students every year, as of 2022. The University transitioned to distance learning in the middle of the Winter 2020 (WN20) semester. The majority of university courses were taught remotely in Fall 2020 and Winter 2021, and many returned to in person teaching in Fall 2021. A small percentage of courses were hybrid modality from Fall 2020 to Winter 2022. The proportion of STEM course sections in each learning modality by semester are presented in Figure 1.

2.2 Empirical strategy

We estimate the association between distance learning and grade outcomes for students who are low-income and first-generation by contrasting the difference in educational outcomes between in person and distance learning modality in students who are low-income and first-generation relative to that of students who are non-low-income and non-first-generation. Thus our method focuses on the interaction between distance learning and low-income or first-generation status. In addition to students who are low-income and first-generation, we are interested in lower performing students within these categories. To estimate the association between distance learning and grade outcomes for the lower performing students at the lower quintile, we employ the expected shortfall (ES) regression which allows for this specification. ES regression allows us to study the average outcome for the students whose outcomes fall in the bottom quintile of the entire population. More details about ES regression can be found in Section 4.

Second, we estimate the outcomes of interventions that provide increased student attention, student-peer and student-instructor interaction, particularly for students underrepresented in higher education and STEM, taking advantage of the university's course initiatives implemented in a large introductory physics course. We implement a three-way-interaction strategy within the expected shortfall regression, contrasting differences between students who are low-income and their non-low-income peers and students who are first-generation and their non-first-generation peers enrolled within these special course sections versus in standard sections, in distance learning versus in person learning.

In our regressions, we control for other student, course, and term variables and separate the pandemic association with grade values from the distance learning association with grade values.

2.3 Data and definition of outcomes

Our data consist of semester data on student grades for undergraduate students at University between Fall 2016 and Fall 2022. Because classes transitioned to remote midway during the Winter 2020 semester at the onset of the pandemic, this semester is excluded from our analysis. Restricting classes to undergraduate level semester-long classes that follow a typical A-E grading scale, our data comprise 1,256,632 observations. Limiting to STEM courses, our data comprise 675,463 observations. The outcome variable, grade value, is taken as the numerical equivalent of the letter grade given by an instructor to a student. Otherwise, the official letter grade received may be in Satisfactory/Not Recorded or Pass/Fail format. A student's low-income status, is described as low-income if a student reported their household gross income to be in the lowest income bracket (less than $25,000 a year) and non-low-income otherwise. A student's first-generation status is described as first-generation if a student reported their parents' maximum educational attainment level to be less than a Bachelor's degree and non-first-generation otherwise. In our dataset, 4.88% of students are categorized as low-income and 13.0% are categorized as first-generation.

2.4 Association between distance learning and grade outcomes in STEM courses

Panel A of Table 1 presents estimates of the association between distance learning and grade outcomes (in grade points: 0.0-4.0) for low-income versus non-low-income students in STEM courses. Our results suggest that there may exist differences in the association between distance learning and educational outcomes for low-income students in the bottom quintile of students in terms of grade values. Among the bottom quintile of low-income students and the bottom quintile of non-low-income students, low-income students show a significant grade difference of –0.114 ($p<0.001$; CI: –0.181, –0.047) points, on average, relative to their non-low-income peers during distance learning.

Panel B of Table 1 presents estimates of the association between distance learning and grade outcomes for first-generation versus non-first-generation students in STEM courses. Similar to the first model, the table suggests that there exists differences in the association between distance learning and educational outcomes for the bottom quintile of first-generation students. We found that the bottom quintile of first-generation students show a significant grade difference of -0.064 ($p=0.003$; CI: -0.106, -0.023) points, on average, relative to the bottom quintile of non-first-generation students during distance learning. For both first-generation and low-income students in the bottom quintile, there is no significant link between hybrid learning and grade outcomes as opposed to in person learning.

The association between distance learning and grade outcomes for the bottom quintile of students in STEM courses can also be seen in Figure 2. We observe that the association between distance learning and grade outcomes is significantly negative for both the bottom quintile of non-low-income and non-first-generation students and the bottom quintile of low-income and first-generation students, but the estimate is much more negative for low-income and first-generation students.

We detect a small disparity (around -0.025) for low-income students but not for first-generation students in the mean results as shown in Supplementary Table 8. Results for all courses are displayed in Supplementary Table 9 and Supplementary Figure 4. Results for STEM courses from a regression including interactions for both low-income and first-generation status are displayed in Supplementary Table 12 and Supplementary Figure 3. There is a significant negative association between distance learning and grade outcomes for the bottom quintile of non-low income and non-first generation, only low-income, only first-generation, and both low-income and first-generation students. The additional association between distance learning and grade outcomes on only low-income, only first-generation, and both low-income and first-generation students is significantly negative. The results including interactions for both low-income and first-generation status for all courses are displayed in Supplementary Table 13 and Supplementary Figure 5. We additionally considered the association between distance learning, hybrid learning, and grade outcomes by sex and by underrepresented minority status. The results are in Supplementary Table 1 in Supplementary Information A.1 and Supplementary Table 2 and Supplementary Figure 1 in Supplementary Information A.2, respectively. As COVID-induced distance learning is intertwined with factors such as at-home conditions, we considered the association between distance learning and grade outcomes in courses that had distance learning after most courses returned to in-person on campus. The results are in Supplementary Tables 5-6 in Appendix A.4.

2.5 Association between distance learning and grade outcomes by subject category

In addition to across all STEM courses, we further considered the association between distance learning and grade outcomes for courses in different subject categories. Specifically, we considered the following subject categories: Physical & Natural Sciences, Social Sciences, Engineering, Medicine & Health, and Humanities, Arts & Languages. All Physical & Natural Sciences and Engineering courses are considered STEM, while some courses in Medicine & Health and Social Sciences and almost no courses in Humanities, Arts & Languages are considered STEM. The association between distance learning, low-income or first generation status, and grade outcomes for the bottom quintile of students in these groups is presented in Figure 3. For Physical & Natural Sciences and Engineering, we observe similar results for low-income and first-generation students as in our main results for all STEM courses. The negative association between distance learning, low-income or first-generation status, and grade outcomes is generally largest in Physical & Natural Sciences, Engineering, and Medicine & Health courses, compared to the Social Sciences and Humanities, Arts & Languages. Tables presenting estimates of the association between distance learning and grade outcomes comparable to that in Table 1 are in Supplementary Table 10 in Supplementary Information B.

2.6 Association between the COVID-19 pandemic and grade outcomes in STEM courses

In the previous sections, we considered the association between distance learning and grade outcomes, controlling for associations with the COVID-19 pandemic. Specifically, we include in the regressions an indicator of post Winter 2020 semesters as well as its interaction with low-income and first-generation statuses to allow for differential associations between the pandemic and grade outcomes on different subgroups of students. The results are presented in Supplementary Figure 6 in Supplementary Information B. The figure shows clearly that there exists a negative association between the pandemic and student learning outcomes of all income levels and regardless of whether they are first-generation college students or not. However, the link is much more substantial for first-generation students. The association between the COVID-19 pandemic and grade outcomes for all courses and for the subjects considered in Section 2.5 is presented in Supplementary Figure 7 in Supplementary Information B and Supplementary Figure 9 in Supplementary Information B, respectively.

2.7 Is an intervention associated with smaller disparity between groups?

In this section, we examine the link between an intervention that aims to increase student-peer interaction and student-instructor interaction on the relationship between distance learning and the grade outcomes of underrepresented students. We consider an introductory physics course that is offered in both Winter and Fall semesters, and enrolls on average 582 students per semester. This course is offered in multiple sections. Besides the standard sections, starting from Fall 2019, the course includes two sections of students as part of the Foundational Course Initiative (FCI). The FCI sections provide students with greater access to instructor support, more peer interaction by having small groups within a large class and frequent discussion and group/individual work instead of lectures.

FCI sections consist of around 200 students per term and are about a third of the total students in the course starting in Fall 2019. All sections (FCI, standard) offered in person instructions before Winter 2020, and shifted to distance learning in Fall 2020 and Winter 2021. While FCI sections were in person the following semester (Fall 2021), standard sections remained distance and only shifted back to in person instructions in Winter 2022.

Our physics course data comprise 7,373 observations, 1,212 of which are for FCI sections. The demographics of the FCI sections are approximately the same as those of the standard sections. A brief summary of the students in different sections is presented in Table 2 in Section 4.

As all sections (FCI, standard) experienced both in person and distance learning, and the learning modality is mostly syncronized across all sections (except for one semester, Fall 2021), we can compare the relationship between distance learning and grade outcomes based on the type of sections. We continue to use the instructor inputted grade as our outcome as before. In this section, we conduct expected shortfall regressions with three-way interaction terms to examine how the innovative course sections (i.e., FCI), moderate the association between distance learning and grade outcomes for low-income and first-generation students.

The difference in association between distance learning and grade outcomes for the regular sections and FCI sections is presented in Figure 4. For the bottom quintile of non-low-income and non-first-generation students, the association between distance learning and grade outcomes is not statistically significantly different between regular sections and FCI sections (effect size=0.133; p=0.179; CI: -0.061, 0.327 and effect size=0.099; p=0.333; CI: -0.102, 0.299, respectively). For first-generation students, the association effect size increases from standard to FCI and becomes significantly positive in the FCI sections (effect size=0.792; p=0.010; CI: 0.188, 1.396). For low-income students, we also observe a increase in the effect size for the association between distance learning and grade outcomes from standard to FCI section types (effect size=1.063; p=0.021; CI: 0.159, 1.968). In other words, under the intervention (i.e., FCI), the negative link between distance learning and grade outcomes in first-generation and low-income students is reduced.

The intervention is not linked to a statistically significant association between the COVID-19 pandemic and grade outcomes. The results are presented in Supplementary Figure 8 in Supplementary Information B.

3 Discussion

This paper presents estimates of the educational gap between lower performing students who are low-income or first-generation and their non-low-income/non-first-generation peers in COVID-induced distance learning. Using over 600,000 student records data from a large public university, we provide evidence that there exists a negative association between COVID-induced distance learning and grade outcomes for students who are low-income and first-generation, particularly those in the lower quintile, in STEM courses. We do not find such association at the mean. Additionally, we find that innovative course initiatives that provide students will increased peer interaction as well as student-instructor interaction are linked to a lowered negative association observed between distance learning during the pandemic and grade outcomes for students who are low-income and first-generation.

This paper contributes to the growing literature studying the association between distance learning and academic outcomes during COVID-19. Several papers have explored the relationship between distance learning, student experiences [66–68] and academic outcomes during COVID-19. Many studies considering academic outcomes focus on primary or secondary education [69–72]. Notably, [71] observed learning loss and widened achievement gaps in primary education, while [72] reported increased dropout risks and decreased test scores in secondary education in Brazil. Studies that focus on higher education tend to be smaller scale [73–75]. Among higher education studies, [73] found no significant differences in grades between online and in-person learning in STEM courses including biology, chemistry, physics, mathematics, and statistics, attributing it to instructors' proactive course adjustments. [76] found higher grades overall and mitigated equity gaps for underrepresented students in online learning for an introductory biology course series, and hypothesized it may be due to instructors changing grading practices. Conversely, an experiment by [74] revealed lower final grades in distance learning, particularly affecting academically at-risk students. Analyzing data from 11,000 academic records at Queens College, [75] discovered that lower-income students in the bottom quartile outperformed their higher-income peers due to flexible grading policies. However, no advantage was found for top-performing lower-income students, and without flexible grading policies, there was a decline in GPA. Larger-scale studies like those conducted by [77] and [78], focusing on statewide community college systems, highlighted a decrease in course completion, particularly for students with lower GPAs. [78] noted a decrease in course completion but an increase in A grades, attributing it to instructor leniency in grading during the pandemic. Our paper is a large-scale higher education study that focuses on disparities in STEM academic outcomes due to distance learning in lower performing students who are low-income and first-generation. Additionally, our study explores an intervention that reduces the gap in achievement from distance learning for disadvantaged students.

Students considered low-income and first-generation may face greater academic challenges in distance learning, attributed to limited access to resources and familial support [27, 29, 30]. Additionally, they are less likely to engage in learning experiences that foster academic success, such as collaborative group studying, interactions with faculty and peers, and utilization of support services [15, 17–26]. Therefore, providing additional support from instructors or learning assistants and encouraging increased peer engagement can positively relate to students' academic performance. The intervention (FCI) we examine features smaller class styles by assigning students to work in smaller groups facilitated by learning assistants, thereby fostering greater peer interactions as well as student-instructor interactions.

Several other courses have been re-designed as part of FCI, however some may redesign all sections of the course or change a section fundamentally such that FCI and non-FCI sections are not comparable. For example, switching to written assignments instead of exams. Additionally, the majority of these courses began their remodel after the onset of the pandemic and switch to distance learning. The impact of these initiatives in other courses is worth exploring.

Other strategies that could enhance the learning experience for students considered low-income and first-generation engaged in distance learning involve implementing systems for monitoring student progress [9]. These systems enable both instructors and students to proactively address and enhance performance well before a student faces potential failure. One such system, ECoach, empowers students to monitor their progress, receive personalized feedback, and access course tips and exam playbooks. Previous research has investigated the efficacy of ECoach in traditional STEM and economics courses conducted in-person [79, 80], revealing positive effects on students' academic outcomes. Notably, a study by [79] demonstrated that first-generation students derived greater benefits from the ECoach exam playbook resource compared to their non-first-generation counterparts. It is important to note that in both studies, students independently utilized ECoach tools. Considering the promising outcomes observed, further exploration of the advantages of using ECoach in a distance learning environment, with incentives for universal adoption among students in a study, holds potential.

Initiatives to redesign courses, like FCI, have been explored at a number of universities. These include the University of Pennsylvania Structured, Active, In-class learning (SAIL), UNC Chapel Hill Associate of American Universities (AAU) STEM Project, Purdue University IMPACT Project, Cornell University Active Learning Initiative (ALI), and TRESTLE, a multi-institution (Univerity of Kansas, Indiana University, Queen's University at Kingston, University of California-Davis, University of Colorado-Boulder, University of Texas at San Antonio, University of British Columbia) NSF-funded project to promote improvement of STEM education at research universities [81]. Many efforts focus on reforming science education, particularly introductory and required courses. One trait frequently included in evidence-based course redesigns is the emphasis on active learning and interaction with classmates, especially through the creation of small groups or teams, similar to the intervention in the physics course we examined. The popularity of this pedagogical method in courses is due to its strong positive outcomes for students in terms of their performance in and perception of the course [82–85]. Brown University's Associate of American Universities (AAU) undergraduate STEM education initiative project aimed to improve retention in introductory and required science courses, and redesigned 11 courses by integrating problem solving sessions into recitations, encouraging engagement and collaboration with peers [86]. These initiatives have also been implemented and studied during COVID-induced distance learning. As a part of the Active Learning Initiative (ALI) at Cornell University, instructors implemented team-based learning (TBL) first in an in-person life sciences course and later both adapted the course with TBL to a smaller online platform and utilized TBL when transitioning the in-person course to online during the onset of the pandemic [64]. They found that TBL enhanced the student experience in the online course and students had high retention and achievement with online teaching [64]. Another ALI at Cornell investigated student performance during the pandemic and found that teaching methods that promote active engagement, such as small group activities, can mitigate the negative effect incurred in online classes during the pandemic [65].

Our study is limited to one university, so there is a need for broader data collection so that large scale studies across universities can be done in the future to understand the prevalence of disparity in higher education during distance learning. The University's response to the pandemic aligns with the typical response of other large universities in the United States. Campus closed in March 2020 and did not reopen until Fall 2020, and the majority of courses shifted to distance learning until Fall 2021. In Fall 2020, the university's percent of undergraduates exclusively in distance education is similar to the median of its comparison group, which includes most Ivy Leagues, University of California system schools, and public universities such as Indiana University-Bloomington, University of Minnesota-Twin Cities, and University of Wisconsin-Madison [87]. However, the percent of undergraduates in at least one but not all distance education courses is much higher at the University at 61% compared to 35% for the comparison group. In Fall 2021, the percent of undergraduates in at least one but not all distance courses is 46% compared to 38% for the comparison group and the percent not in any distance education is 54% versus 59% [88]. Although the response to the pandemic and adoption of distance learning is relatively similar, our findings may not generalize to other comparable universities due to differences in factors influencing grade outcomes such as academic culture, student body, and grading scheme. As of 2015-2016, about 20% of students enrolled in undergraduate education were in poverty (family income for family of four less than $25,696), and for Very Selective four-year universities about 13% were in poverty [89]. Our definition of low-income as family income less than $25,000, based on the the poverty guidelines updated periodically in the Federal Register by the U.S. Department of Health and Human Services under the authority of 42 U.S.C. 9902(2) [90], includes In Poverty and Near Poverty categories defined by Pew Research Center. About 56% of undergraduates nationally were first-generation, defined as neither parent having a bachelor's degree [91]. In our dataset, about 5% of students are considered low-income and 13% are considered first-generation, which is much lower than the national statistics. Thus, nationally there may be a higher or more detectable association between distance learning and grade outcomes in students considered low-income and first-generation.

Our study considers distance learning in the context of the pandemic, which can be accompanied by and difficult to separate from factors such as disruptions in students' everyday life, differing at-home conditions, and carry-over effects such as potential loss of knowledge in pre-requisite courses. As a limitation, we cannot completely distinguish the association between distance learning and academic outcomes from these factors. Beyond the context of the pandemic, many universities in the United States and around the world have shown recent enthusiasm for adopting distance learning [92–94]. In STEM education in particular, distance learning strategies are receiving increased attention [40, 58, 95–97]. The link between distance learning and academic outcomes remains inconclusive, as various studies present differing perspectives. Some research suggests no significant difference or even improved outcomes in comparison to traditional in-person learning [38–40, 98]. Conversely, other studies suggest that student learning and performance may be somewhat lower in a distance setting when compared to face-to-face environments [42, 99, 100]. Proponents of distance education assert that online courses not only provide students with greater and more convenient access to coursework but also serve as cost-effective instructional alternatives for universities [101, 102]. As online courses gain popularity among both universities and students, there is a crucial need to thoroughly investigate the diverse patterns in academic outcomes during remote learning, especially among the most vulnerable student populations.

4 Methods

The study has received approval from the University of Michigan's The Health Sciences and Behavioral Sciences Institutional Review Board and the data are procured through a Memorandum of Understanding (MOU) agreement with the University's enrollment management office to ensure strict protection of student privacy.

Data. Our data set consists of administrative data and educational outcomes for all students enrolled at the University from the mid-1990s through 2022. In our main sample of STEM courses for the years 2016 to 2022, we have a total of 675,463 data points for 1200 unique courses and 66,461 unique students. Of these, approximately 43% of the data points are after Winter 2020. Additionally, information about the introductory physics course sections were made available through the university's collection of historical syllabi.

Measures and definitions. We define grade values, the outcome variable of interest, as the numerical equivalent of the letter grade given by an instructor to a student (A+/A=4.0, A-=3.7, B+=3.3, B=3.0, B-=2.7, C+=2.3, C=2.0, C-=1.7, D+=1.3, D=1.0, D-=0.7, E=0.0). The instructor inputted grade is the grade given by an instructor to a student; the official grade that appears on a student's transcript is the translated value of the instructor inputted grade as defined by the school or college grading policy. Official grades may take other forms other than a letter grade. Due to COVID-19, official grades may be chosen to be masked by students as Satisfactory/Not Recorded - COVID.

Courses are categorized as STEM by their instructional area based on the 2023 U.S. Department of Homeland Security (DHS) STEM Designated Degree Program List [103]. The list designates all Engineering, Biological and Biomedical Sciences, Mathematics and Statistics, and Physical Sciences (determined by the Department of Education's Classification of Instructional Programs) programs as STEM, and also includes some programs in related fields such as Natural Resources and Conservation, Education, Psychology, etc. For categorizing instructional areas into subject categories, Physical & Natural Sciences include life sciences, physics, chemistry, earth science, astronomy, and mathematics. Engineering includes all fields of engineering, as well as information and technology related subjects. Social Sciences include social and behavioral sciences such as sociology, economics law, anthropology, business, etc. Medicine and Health include areas in Kinesiology, Pre-Medicine, Nursing, Pharmacy, Dentistry, and Public Health. Based on the DHS Designated Degree Program List, all Physical & Natural Sciences and Engineering divisions, some Social Sciences or Humanities divisions such as archaeology and psychology, and some Medicine and Health divisions such as kinesiology, pharmacology, immunology, and biological sciences are designated STEM.

For the student categories of interest, a student's low-income status is defined as estimated gross family income less than $25,000 and first-generation status as parent's maximum education level less than a Bachelor's degree. Estimated gross family income and parent's maximum education level are self-reported in a student's application for college admission; students that do not report these are considered non-low-income or non-first-generation. A sensitivity analysis of our results when excluding these observations where household income or parent's educational level are not reported is in Supplementary Information A.3 Tables 3-4 and Supplementary Figure 2.

Of the unique students in our main data set, 4.88% are considered low-income and 13.0% are considered first-generation. Among low-income students, 52.0% are first-generation, and among first-generation students, 19.6% are low-income. A brief summary of the students in all considered courses and in the introductory physics course examined in Section 2.7 is presented in Table 2.

Intervention. The intervention we considered was FCI sections in a large introductory physics course. We provide a brief description of how this program appears in the physics course. Starting in 2018, FCI partnered with the physics course over a three year pilot period. As a result of the partnership, starting from Fall 2019 onward, two sections of the physics course under study were transformed into a Studio Model , in which instructors used the same curriculum (e.g., same teaching materials) and students were held up to the same course requirements as those in the standard sections. The main difference, however, is that it created a radically different student experience. Each FCI section is split into several neighborhoods of students who spend the whole term together. Additionally, within a neighborhood, students work in small groups of three and cycle through groups throughout the term such that every student in a neighborhood will have worked with every other student by the end of the semester. Each neighborhood is directly overseen by a undergraduate learning assistant. A large portion of lecture time is dedicated group work within these groups which during distance learning is done synchronously on Gather Town. The rest of the lecture is review or preview and individual work periods. Regular sections meet for one hour lectures four times a week, while FCI sections meet twice a week for two hours each. Moreover, each section employs five additional learning assistants, a graduate student instructor, and a faculty member, all part of the instruction team. In this way, the FCI section increases the students' interactions with one another and with instructors, and results in a larger instructor/assistant-to-student ratio. The inclusion of this type of section was maintained after the three year partnership with FCI ended.

Furthermore, one of the remaining sections of the physics is part of the Comprehensive Studies Program (CSP). CSP sections consist of about 20 students per term, while FCI sections have the same sizes as standard sections. We focus our discussion on FCI instead of CSP, because the latter is a small scale intervention representing no more than 5% of the total students enrolled in the physics course, while FCI is a larger-scale intervention with two sections of regular size classes. Moreover, FCI is a more recent innovation with primarily in-class transformations, while CSP is an existing program started in the 1980s which features additional outside resources for students part of the program such as advising and tutoring. However, we control for the existence of CSP sections in our regressions.

Empirical strategy. We are interested in contrasting the difference in education outcomes between in-person and distance learning modality in low-income and first-generation students relative to that in non-low-income and non-first-generation students. Thus, our method focuses on the interaction between distance learning and low-income or first-generation status. Ordinary least squares is a baseline approach for fitting linear models and focuses on inferring the conditional mean of the response given the predictors. However, more aspects than the mean of the conditional distribution of the response given predictors are of interest. In particular, we are interested in lower performing students within these categories. Thus, we utilize expected shortfall (ES) regression which allows for this specification.

The quantity of interest for ES regression is the expected shortfall, compared to the mean for ordinary least squares regression. If we consider a single variable, such as grades, the 0.20-ES refers to the average grade for the sub-population of students whose grades fall below the 0.20-quantile of the entire population, where the 0.20-quantile of the grade outcome refers to the highest grade of those who have the 20% lowest grades among the entire population. In other words, ES gives us the average outcome for the lowest-performing students. To extend this concept to a regression setting, we focus on the average outcomes for the students who fall below a certain threshold (at a specific quantile level) conditional on a given set of covariates. Specifically, ES regression allows us to estimate the relationship between an explanatory variable (e.g. distance learning) and the average outcome for the lowest-performing students, while controlling for other relevant factors/covariates.

We estimate the association between distance learning and educational outcomes for disadvantaged students with a focus on the average performance of the bottom quintile using the following specification:

$$\begin{aligned} \mathrm{E}[Y_{ict}|Y_{ict} \le Q_\tau(Y_{ict}|\mathbf{X}_{ict}, \mathbf{W}_{ict}), \mathbf{X}_{ict}, \mathbf{W}_{ict}] = \\ \alpha_0 + \beta_1 D_i + \beta_2 \text{Distance}_{ct} + \beta_3 \text{Hybrid}_{ct} + \\ \beta_4 \text{Post-WN20}_{ct} + \beta_5 D_i \cdot \text{Distance}_{ct} + \\ \beta_6 D_i \cdot \text{Hybrid}_{ct} + \beta_7 D_i \cdot \text{Post-WN20}_t + \boldsymbol{\gamma} \mathbf{W}_{ict} \end{aligned} \quad (1)$$

where Y_{ict} is an outcome for student i in course c in term t, $Q_\tau(Y_{ict}|\mathbf{X}_{ict}, \mathbf{W}_{ict})$ denotes the conditional quantile at quantile level τ, and $\mathrm{E}[Y_{ict}|Y_{ict} \le Q_\tau(Y_{ict}|\mathbf{X}_{ict}, \mathbf{W}_{ict}), \mathbf{X}_{ict}, \mathbf{W}_{ict}]$ is the conditional ES at level τ, which can be interpreted as the average outcome, given covariates $\mathbf{X}_{ict}$ and $\mathbf{W}_{ict}$, for the subpopulation whose outcomes fall below the τ-quantile conditional on covariates $\mathbf{X}_{ict}$ and $\mathbf{W_{ict}}$. Model (1) utilizes the conditional ES, targeting the lower quintile conditional on specified covariates rather than truncating the students at the bottom of the performance distribution. The advantage of ES regression over alternatives that also consider the entire conditional distribution such as quantile regression is that it can provide information about the average in the tail of a distribution, in our case the bottom quintile, rather than only providing information about specific points along a distribution. More details about the use of quantiles in regression analysis can be found in [104] and in depth discussion of ES and its mathematical properties can be found in [105] and [106].

The vector $\mathbf{X}_{ict}$ includes main and interaction variables $\{D_i, \text{Distance}_{ct}, \text{Hybrid}_{ct}, \text{Post-WN20}_{ct}, D_i \cdot \text{Distance}_{ct}, D_i \cdot \text{Hybrid}_{ct}, D_i \cdot \text{Post-WN20}_t\}$, where D_i is an indicator variable coded to 1 if student i is in a disadvantaged group such as low-income or first-generation, Distance_{ct} is an indicator variable coded to 1 if course c in term t is distance learning, Hybrid_{ct} is an indicator variable coded to 1 if course c in term t is hybrid, and Post-WN20_t is an indicator variable coded to 1 if term t is after the Winter 2020 term. The covariates matrix $\mathbf{W}$ includes the following student, course, and term attributes: indicator variables for male, underrepresented minority status, part-time student status, overtime status (more than 18 credit hours in a term), the previous term cumulative GPA, indicators for first term attended, class standing (i.e., Sophomore), incomplete status, unofficial withdrawal status, repeating class, winter term, the log scaled total enrollment for the course, and average class GPA excluding student i.

We use this specification to measure the disparate association between distance learning and changes due to COVID-19 and the grade values of low-income and first-generation students, particularly those in the lower quintile of academic performance. The estimates are from ES regressions. The 95% confidence intervals are obtained following [106]. We consider $\tau = \{0.20, 1\}$, where $\tau = 1$ is equivalent to an ordinary least squares regression. The ES regression estimator is asymptotically normal [106] thus the p-value is determined from a two-sided one-sample Z-test where the estimate is compared to zero and the test statistic is calculated as the ES regression estimate divided by the standard error (obtained following [106]). The estimate of the difference in association between distance learning and grade values for the bottom $(\tau \cdot 100)$% of $D = 1$ students compared to the bottom $(\tau \cdot 100)$% of $D = 0$ students would be β_5, and the estimate of the difference in grade values between the bottom $(\tau \cdot 100)$% of $D = 1$ students and bottom $(\tau \cdot 100)$% of $D = 0$ students in distance learning would be $\beta_1 + \beta_5$. We considered additional analyses using $\tau = \{0.1, 0.15, 0.25, 0.5\}$ and generally found significant results for $\tau \leq 0.25$.

We estimate how an intervention in the form of innovative course initiatives (i.e. FCI) relates to the association between distance learning and educational outcomes by utilizing three-way-interaction terms, in which we contrast differences between disadvantaged and non-disadvantaged students within course sections that adopted an innovative instruction style versus those within standard course sections, in distance and in person learning. As the course we considered did not have any sections adopting hybrid learning modality and did not have any students with an unofficial withdrawal, we excluded these two variables. We estimate the association between grade outcomes and distance learning and the pandemic on disadvantaged students and its interactions with non-standard course sections through a three-way-interaction strategy using the following specification:

$$
\begin{aligned}
\mathrm{E}[Y_{ist}|Y_{ist} \leq Q_\tau(Y_{ist}|\mathbf{X}_{ist}, \mathbf{W}_{ist}), \mathbf{X}_{ist}, \mathbf{W}_{ist}] = \\
\alpha_0 + \beta_1 D_i + \beta_2 \text{Distance}_{st} + \beta_3 \text{Post-WN20}_{st} + \\
\beta_4 \text{FCI}_{st} + \beta_5 \text{CSP}_{st} + \beta_6 D_i \cdot \text{Distance}_{st} + \\
\beta_7 D_i \cdot \text{Post-WN20}_t + \beta_8 \text{Distance}_{st} \cdot \text{FCI}_{st} + \\
\beta_9 \text{Distance}_{st} \cdot \text{CSP}_{st} + \beta_{10} \text{Post-WN20}_{st} \cdot \text{FCI}_{st} + \\
\beta_{11} \text{Post-WN20}_{st} \cdot \text{CSP}_{st} + \beta_{12} D_i \cdot \text{FCI}_{st} + \\
\beta_{13} D_i \cdot \text{CSP}_{st} + \beta_{14} D_i \cdot \text{Distance}_{st} \cdot \text{FCI}_{st} + \\
\beta_{15} D_i \cdot \text{Distance}_{st} \cdot \text{CSP}_{st} + \\
\beta_{16} D_i \cdot \text{Post-WN20}_{st} \cdot \text{FCI}_{st} + \\
\beta_{17} D_i \cdot \text{Post-WN20}_{st} \cdot \text{CSP}_{st} + \boldsymbol{\gamma} \mathbf{W}_{ist}
\end{aligned}
\tag{2}
$$

where Y_{ist} is an outcome for student i in section s in term t, FCI_{st} is an indicator variable coded to 1 if section s in term t is an FCI section, CSP_{st} is an indicator variable coded to 1 if section s in term t is a CSP section, and $\mathbf{W}_{ist}$ follows that in equation (1) excluding unofficial withdrawals and by section s rather than course c.

5 Data availability

Currently, the LARC Data Set is available to University of Michigan (U-M) investigators who have obtained Institutional Review Board (IRB) approval and signed a memorandum of understanding describing their research interests. Investigators not affiliated with the University of Michigan must adhere to the established data request protocols of the University of Michigan to gain access to data. Investigators should contact student.data.request@umich.edu to request access to data. The expected time-frame for response to access requests depends on the the scope of the request. For accepted data requests, the timeline for data availability will be outlined in the data user agreement. More information about accessing the data can be found here: https://enrollment.umich.edu/data/learning-analytics-data-architecture-larc. Cleaned data are available from the authors upon university approval for LARC data. Individuals interested in obtaining this data should follow above steps to obtain approval from the University of Michigan. Source Data are provided with this paper.

6 Code availability

Code to perform the expected shortfall regression method is available in the Supplementary Code.

References

[1] United Nations Educational, Scientific and Cultural Organization. Education: From disruption to recovery (2020). URL https://www.unesco.org/en/covid-19/education-response.

[2] National Center for Educational Statistics. 2019-20 National postsecondary student aid study (NPSAS:20): First look at the impact of the coronavirus (COVID-19) pandemic on undergraduate student enrollment, housing, and finances (preliminary data). Tech. Rep., U.S. Department of Education, Institute of Education Sciences (2021).

[3] National Center for Education Statistics. Undergraduate Enrollment. *Condition of Education*. Tech. Rep., U.S. Department of Education, Institute of Education Sciences (2023).

[4] Daymont, T., Blau, G. & Campbell, D. Deciding between traditional and online formats: Exploring the role of learning advantages, flexibility, and compensatory adaptation. *Journal of Behavioral and Applied Management* **12**, 156 (2011).

[5] Broadbent, J. & Poon, W. L. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education* **27**, 1–13 (2015).

[6] Picciano, A. G. Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous Learning Networks* **6**, 21–40 (2002).

[7] Jimenez, L. *Student assessment during COVID-19* (Center for American Progress, 2020).

[8] Cahalan, M. *et al.* Indicators of Higher Education Equity in the United States: 2022 Historical Trend Report. Tech. Rep., The Pell Institute for the Study of Opportunity in Higher Education, Council for Opportunity in Education (COE), and Alliance for Higher Education and Democracy of the University of Pennsylvania (PennAHEAD), Washington, DC (2022).

[9] Engle, J. & Tinto, V. Moving beyond access: College success for low-income, first-generation students. Tech. Rep., The Pell Institute for the Study of Opportunity in Higher Education (2008).

[10] Berkner, L. & Chavez, L. Access to post-secondary education for 1992 high school graduates. Tech. Rep., National Center for Education Statistics, Washington, DC (1997).

[11] Chen, X. First-generation students in post-secondary education: A look at their college transcripts. Tech. Rep., National Center for Education Statistics, Washington, DC (2005).

[12] Choy, S. Low-income students: Who they are and how they pay for their education. Tech. Rep., National Center for Education Statistics, Washington, DC (2000).

[13] Choy, S. Students whose parents did not go to college: Postsecondary access, persistence, and attainment. Tech. Rep., National Center for Education Statistics, Washington, DC (2001).

[14] Horn, L. & Nunez, A. Mapping the road to college: First-generation students' math track, planning strategies, and context of support. Tech. Rep., National Center for Education Statistics, Washington, DC (2000).

[15] Nunez, A. & Cuccaro-Alamin, S. First-generation students: Undergraduates whose parents never enrolled in postsecondary education. Tech. Rep., National Center for Education Statistics, Washington, DC (1998).

[16] Warburton, E., Bugarin, R. & Nunez, A. Bridging the gap: Academic preparation and postsecondary success of first-generation students. Tech. Rep., National Center for Education Statistics, Washington, DC (2001).

[17] Astin, A. *What matters in college: four critical years revisited* (Jossey-Bass, San Francisco, 1997).

[18] Cabrera, A., Nora, A. & Castaneda, M. The role of finances in the persistence process: A structural model. *Research in Higher Education* **33**, 571–593 (1992).

[19] Billson, J. & Terry, M. In search of the silken purse: Factors in attrition among first-generation students. *College and University* 57–75 (1982).

[20] Lohfink, M. & Paulsen, M. Comparing the determinants of persistence for first-generation and continuing-generation students. *Journal of College Student Development* **46**, 409–428 (2005).

[21] Pascarella, E. T., Pierson, C. T., Wolniak, G. C. & Terenzini, P. T. Experiences and outcomes of first-generation students in community colleges. *Journal of College Student Development* **44**, 420–429 (2003).

[22] Pascarella, E. T., Pierson, C. T., Wolniak, G. C. & Terenzini, P. T. First-generation college students: Additional evidence on college experiences and outcomes. *The Journal of Higher Education* **75**, 249–284 (2004).

[23] Pike, G. R. & Kuh, G. D. First- and second-generation college students: A comparison of their engagement and intellectual development. *The Journal of Higher Education* **76**, 276–300 (2005).

[24] Richardson, R. C. & Skinner, E. F. in *Helping first generation minority students achieve degrees* (eds Zwerling, L. S. & London, H. B.) *First Generation College Students: Confronting the Cultural Issues* (Jossey-Bass Publishers, San Francisco, CA, 1992).

[25] Terenzini, P. T., Springer, L., Yaeger, P. M., Pascarella, E. T. & Nora, A. First generation college students: Characteristics, experiences, and cognitive development. *Research in Higher Education* **37**, 1–22 (1996).

[26] Terenzini, P. T., Cabrera, A. F. & Bernal, E. M. *Swimming Against the Tide: The Poor in American Higher Education* (College Board, New York, 2001).

[27] Means, B. & Neisler, J. Unmasking inequality: STEM course experience during the COVID-19 pandemic. *Digital Promise* (2020).

[28] Means, B. & Neisler, J. Suddenly online: A national survey of undergraduates during the COVID-19 pandemic. *Digital Promise* (2020).

[29] Barber, P. H. *et al.* Disparities in remote learning faced by first-generation and underrepresented minority students during COVID-19: Insights and opportunities from a remote research experience. *Journal of Microbiology and Biology Education* **22** (2021).

[30] Goudeau, S., Sanrey, C., Stanczak, A., Manstead, A. & Darnon, C. Why lockdown and distance learning during the COVID-19 pandemic are likely to increase the social class achievement gap. *Nat Hum Behav* **5**, 1273–1281 (2021).

[31] Deslauriers, L., Harris, S., Lane, E. & Wieman, C. Transforming the lowest-performing students: an intervention that worked. *Journal of College Science Teaching* **41**, 80–88 (2012).

[32] Freeman, S. *et al.* Prescribed active learning increases performance in introductory biology. *CBE Life Sci Educ.* **6**, 132–139 (2007).

[33] Jensen, P. A. & Moore, R. Students' behaviors, grades and perceptions in an introductory biology course. *American Biology Teacher* **70**, 483–487 (2008).

[34] Jensen, P. A. & Moore, R. What do help sessions accomplish in introductory science courses? *Journal of College Science Teaching* **38**, 60–64 (2009).

[35] Moore, R. Who does extra-credit work in introductory science courses? *Journal of College Science Teaching* **34**, 12–15 (2005).

[36] Bowman, N. A. & Jang, N. What is the purpose of academic probation? Its substantial negative effects on four-year graduation. *Research in Higher Education* **63**, 1285–1311 (2022).

[37] Cahalan, M., Perna, L. W., Yamashita, M., Wright, J. & Santillan, S. 2018 Indicators of higher education equity in the United States: Historical trend report. Tech. Rep., The Pell Institute for the Study of Opportunity in Higher Education, Council for Opportunity in Education (COE), and Alliance for Higher Education and Democracy of the University of Pennsylvania (2018).

[38] Palmer, T. L. & Palmer, S. A. A comparison of online and traditional chemistry lecture and lab. *Chemistry Education Research and Practice* **3**, 47–52 (2002).

[39] Means, B., Toyama, Y., Murphy, R., Bakia, M. & Jones, K. Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. Tech. Rep., US Department of Education (2009).

[40] Chirikov, I., Semenova, T., Maloshonok, N., Bettinger, E. & Kizilcec, R. F. Online education platforms scale college stem instruction with equivalent learning outcomes at lower cost. *Science Advances* **6**, eaay5324 (2020).

[41] Jaggars, S. & Bailey, T. Effectiveness of fully online courses for college students: Response to a Department of Education meta-analysis (2010).

[42] Figlio, D., Rush, M. & Yun, L. Is it live or is it internet? Experimental estimates of the effects of online instruction on student learning. *Journal of Labor Economics* **31**, 763–784 (2013).

[43] Broderick, J. R. & Neufeldt, E. J. John R. Broderick and Ellen J. Neufeldt Column: Filling high-tech jobs requires paradigm shift in higher ed. *Richmond Times-Dispatch* URL richmond.com/opinion/columnists/john-r-broderick-and-ellen-j-neufeldt-column-filling-high-tech-jobs-requires-paradigm-shift/article_41bb67aa-8ca6-522d-85c7-b9f4f15b56f6.html.

[44] Bush, V. *Science, the endless frontier: A report the president on a program for a postwar scientific research* (United States Government Printing Office, Washington, DC, 1945).

[45] Melguizo, T. & Wolniak, G. C. The earnings benefits of majoring in stem fields among high achieving minority students. *Research in Higher Education* **53**, 383–405 (2012).

[46] Xu, Y. J. Career outcomes of stem and non-stem college graduates: Persistence in majored-field and influential factors in career choices. *Research in Higher Education* **54**, 349–382 (2013).

[47] National Science Foundation, National Science Board. Revisiting the STEM workforce. Tech. Rep. (2015).

[48] Carnevale, A. P., Smith, N. & Melton, M. STEM: Science Technology Engineering Mathematics (2011).

[49] Chen, X. STEM attrition among high-performing college students: scope and potential causes. *Journal of Technology and Science Education* **5**, 41–59 (2015).

[50] of Advisors on Science, P. C. & (PCAST), T. Engage to excel: Producing one million additional college graduates with degrees in science, technology, engineering, and mathematics. Tech. Rep., Washington, DC (2012).

[51] Morganson, V. J., Major, D. A., Streets, V. N., Litano, M. L. & Myers, D. P. Using embeddedness theory to understand and promote persistence in STEM majors. *Career Development Quarterly* **63**, 348–362 (2015).

[52] Provencher, A. & Kassel, R. High-impact practices and sophomore retention: Examining the effects of selection bias. *Journal of College Student Retention: Research, Theory and Practice* **21**, 221–241 (2019).

[53] Chen, X. STEM attrition: College students' paths into and out of STEM fields. Statistical Analysis Report. NCES 2014-001. Tech. Rep., Washington, DC (2013).

[54] Crisp, G., Nora, A. & Taggart, A. Student characteristics, pre-college, college and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal* **46**, 924–942 (2009).

[55] Whalen, D. F. & Shelley, M. C. I. Academic success for STEM and non-STEM majors. *Jounral of STEM Education* **11**, 45–60 (2010).

[56] Dika, S. L. & M., D. M. Early experiences and integration in the persistence of first-generation college students in STEM and non-STEM majors. *Journal of Research in Science Teaching* **53**, 368–383 (2016).

[57] Xu, Y. J. Career outcomes of STEM and non-STEM college graduates: Persistence in majored-field and influential factors in career choices. *Res High Educ* **54**, 349–382 (2013).

[58] Skliarova, I., Meireles, I., Martins, N., Tchemisova, T. & Cacao, I. Enriching traditional higher STEM education with online teaching and learnng practices: Student's perspective. *Education Sciences* **12** (2022).

[59] Dickson-Karn, N. M. Student feedback on distance learning in the quantitative chemical analysis laboratory. *Journal of Chemical Education* **97**, 2955–2959 (2020).

[60] Franchi, T. The impact of the COVID-19 pandemic on current anatomy education and future careers: A student's perspective. *Anatomical Sciences Education* **13**, 312–315 (2020).

[61] Perets, E. A. *et al.* Impact of the emergency transition to remote teaching on student engagement in a non-STEM undergraduate chemistry course in the time of COVID-19. *Journal of Chemical Education* **97**, 2439–2447 (2020).

[62] Petillion, R. J. & McNeil, W. S. Student experiences of emergency remote teaching: Impacts of instructor practice on student learning, engagement, and well-being. *Journal of Chemical Education* **97**, 2486–2493 (2020).

[63] Wester, E. R., Walsh, L. L., Arango-Caro, S. & Callis-Duehl, K. L. Student engagement declines in STEM undergraduates during COVID-19 driven remote learning. *Journal of Microbiology & Biology Education* **22** (2021).

[64] Arcila Hernández, L. M., Zamudio, K. R., Drake, A. G. & Smith, M. K. Implementing team-based learning in the life sciences: A case study in an online introductory level evolution and biodiversity course. *Ecol Evol.* **11**, 3527–2536 (2021).

[65] Orlov, G. *et al.* Learning during the COVID-19 pandemic: It is not who you teach, but how you teach. *Economics Letters* **202** (2021).

[66] Mok, K., Xiong, W. & Bin Aedy Rahman, H. COVID-19 pandemic's disruption on university teaching and learning and competence cultivation: Student evaluation of online learning experiences in Hong Kong. *International Journal of Chinese Education* **10** (2021).

[67] Parolin, Z. & Lee, E. Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nat Hum Behav* **5**, 522–528 (2021).

[68] Al-Mahrouqi, T. *et al.* The differential mediating roles of resilience in the relationship between meaningful living and stress among college students during the COVID-19 pandemic. *Sci Rep* **13** (2023).

[69] Angrist, N., Bergman, P. & Matsheng, M. Experimental evidence on learning using low-tech when school is out. *Nat Hum Behav* **6**, 941–950 (2022).

[70] Armstrong-Mensah, E., Ramsey-White, K., Yankey, B. & Self-Brown, S. COVID-19 and distance learning: Effects on Georgia State University School of Public Health students. *Front. Public Health* **8** (2020).

[71] Goldhaber, D. *et al.* The educational consequences of remote and hybrid instruction during the pandemic. *American Economic Review: Insights* **5**, 377–392 (2023).

[72] Lichand, G., Doria, C., Leal-Neto, O. & Fernandes, J. The impacts of remote learning in secondary education during the pandemic in Brazil. *Nat Hum Behav* **6**, 1076–1086 (2022).

[73] Supriya, K. *et al.* Undergraduate biology students received higher grades during COVID-19 but perceived negative effects on learning. *Sec. Educational Psychology* **6** (2021).

[74] Kofoed, M., Gebhart, L., Gilmore, D. & Moschitto, R. Zooming to class? Experimental evidence on college students online learning during COVID-19. *IZA Discussion Paper* (2021).

[75] Rodriguez-Planas, N. COVID-19, college educational outcomes, and the flexible grading policy: A longitudinal analysis. *Journal of Public Economics* **207** (2022).

[76] Zuckerman, A. L., Hardesty, R. A., Denaro, K., Lo, S. M. & Owens, M. T. Effects of remote teaching in a crisis on equity gaps and the constructivist learning environment in an introductory biology course series. *Journal of Microbiology and Biology Education* **22** (2021).

[77] Bird, K., Castleman, B. & Lohner, G. Negative impacts from the shift to online learning through the COVID-19 crisis: Evidence from a statewide community college system. *AERA Open* **8** (2022).

[78] Bulman, G. & Fairlie, R. The impact of COVID-19 on community college enrollment and student success: Evidence from California administrative data. *Education Finance and Policy* **17**, 745–764 (2022).

[79] Chen, P. *et al.* Real-world effectiveness of a social-psychological intervention translated from controlled trials to classrooms. *npj Science of Learning* **7** (2022).

[80] Matz, R. *et al.* Analyzing the efficacy of ECoach in supporting gateway course success through tailored support (2021). Paper presented at LAK21: 11th International Learning Analytics and Knowledge Conference, Irvine, CA, USA, April 2021.

[81] TRESTLE. Trestle home page (2017). https://trestlenetwork.ku.edu/.

[82] Ballen, C. J., Wieman, C., Salehi, S., Searle, J. B. & Zamudio, K. R. Enhancing diversity in undergraduate science: Self-efficacy drives performance gains with active learning. *CBE Life Sciences Education* **16**, 1–6 (2017).

[83] Donovon, D. A., Connell, G. L. & Grunspan, D. Z. Student learning outcomes and attitudes using three methods of group formation in a nonmajors biology class. *CBE Life Sciences Education* **17**, 1–14 (2018).

[84] Kim, K. J., Liu, S. & Bonk, C. J. Online MBA students' perceptions of online learning: Benefits, challenges, and suggestions. *Internet and Higher Education* **8**, 335–344 (2005).

[85] Michaelsen, L. K. & Sweet, M. The essential elements of team-based learning. *New Directions for Teaching and Learning* (2008).

[86] Chasteen, S. V. & Code, W. J. *The Science Education Initiative Handbook* (2018). URL https://pressbooks.bccampus.ca/seihandbook/. This work is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.

[87] National Center for Education Statistics. IPEDS Data Feedback Report 2021: University of Michigan-Ann Arbor. Tech. Rep., National Center for Education Statistics, Washington, DC (2021).

[88] National Center for Education Statistics. IPEDS Data Feedback Report 2022: University of Michigan-Ann Arbor. Tech. Rep., National Center for Education Statistics, Washington, DC (2022).

[89] Pew Research Center. A rising share of undergraduates are from poor families, especially at selective colleges (2019).

[90] Office of the Federal Register, National Archives and Records Administration. 84 FR 1167 - Annual Update of the HHS Poverty Guidelines [Government] (2019).

[91] RTI International. First-generation college students: Demographic characteristics and postsecondary enrollment (2019).

[92] Caruth, G. D. & Caruth, D. L. The impact of distance education on higher education: A case study of the United States. *Turkish Online Journal of Distance Education* **14**, 121–131 (2013).

[93] Kentnor, H. E. Distance education and the evolution of online learning in the United States. *Curriculum and teaching dialogue* **17**, 21–34 (2015).

[94] Seaman, J. E., Allen, I. E. & Seaman, J. Grade increase: Tracking distance education in the United States (2018).

[95] El-Deghaidy, H., Mansour, N., Alzaghibi, M. & Alhammad, K. Context of STEM integration in schools: Views from in-service science teachers. *Journal of Mathematics, Science and Technology Education* **13**, 2459–2484 (2017).

[96] Brancaccio-Taras, L., Mawn, M. V., Premo, J. & Ramachandran, R. Teaching in a time of crisis: Editorial perspectives on adjusting STEM education to the "new normal" during the COVID-19 pandemic. *Journal of Microbiology and Biology Education* **22** (2021).

[97] Alangari, T. S. Online STEM education during COVID-19 period: A systematic review of perceptions in higher education. *EURASIA Journal of Mathematics, Science and Technology Education* **18** (2022).

[98] Fischer, C., Baker, R., Li, Q., Orona, G. & Warschauer, M. Increasing success in higher education: The relationships of online course taking with college completion and time-to-degree. *Education Evaluation and Policy Analysis* **44**, 355–379 (2022).

[99] Bettinger, E. P., Fox, L., Loeb, S. & Taylor, E. S. Virtual classrooms: How online college courses affect student success. *American Economic Review* **107**, 2855–2875 (2017).

[100] Xu, D. & Jaggars, S. Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *The Journal of Higher Education* **85**, 633–659 (2014).

[101] Bartley, S. J. & Golek, J. H. Evaluating the cost effectiveness of online and face-to-face instruction. *Journal of Educational Technology & Society* **7**, 167–175 (2004).

[102] Watson, J. & Gemin, B. Using online learning for at-risk students and credit recovery. Promising practices in online learning (2008).

[103] U.S. Immigration and Customs Enforcement, Washington, DC. *DHS STEM Designated Degree Program List* (2023).

[104] Koenker, R. & Bassett, G. Regression quantiles. *Econometrica* **46**, 33–50 (1978).

[105] Barendse, S. Efficiently weighted estimation of tail and interquantile expectations (2020). URL http://dx.doi.org/10.2139/ssrn.2937665.

[106] He, X., Tan, K. M. & Zhou, W.-X. Robust estimation and inference for expected shortfall regression with many regressors. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **85**, 1223–1246 (2023).

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8 Author Contributions Statement

Authors R.M., J.L., and K.M.T. contributed equally to the work.

9 Competing Interests Statement

All authors are employees or affiliates of the University of Michigan. R.M. was an employee of University of Michigan at the time of the study and is currently a full-time employee of AbbVie. The data and financial support for this research were provided by the University of Michigan.

10 Tables

Table 1: Relationship between educational outcomes and distance learning, COVID-19, and student category for the bottom quintile in STEM courses

	Estimate	95% Confidence Interval	p-value
Panel A: Low-income			
Distance	-0.019	(-0.031, -0.007)	0.002
Hybrid	0.036	(0.011, 0.062)	0.006
Post-WN20	-0.207	(-0.216, -0.199)	<0.001
Low-inc	-0.104	(-0.128, -0.081)	<0.001
Low-inc:Distance	-0.114	(-0.181, -0.047)	<0.001
Low-inc:Hybrid	-0.08	(-0.233, 0.072)	0.304
Low-inc:Post-WN20	-0.04	(-0.086, 0.006)	0.088
Panel B: First-generation			
Distance	-0.016	(-0.028, -0.004)	0.009
Hybrid	0.04	(0.015, 0.065)	0.002
Post-WN20	-0.197	(-0.206, -0.188)	<0.001
First-gen	-0.125	(-0.140, -0.111)	<0.001
First-gen:Distance	-0.064	(-0.106, -0.023)	0.003
First-gen:Hybrid	-0.065	(-0.168, 0.038)	0.216
First-gen:Post-WN20	-0.099	(-0.128, -0.071)	<0.001

The table displays the relationship between distance learning and grade outcomes based on low-income or first-generation status. Panel A shows the main effects of distance learning, hybrid learning, post-WN20, and low-income status and interaction effects comparing the variation in outcomes between the bottom quintile of low-income and non-low-income students for either distance learning, hybrid learning, or pre-WN20 with that between the bottom quintile of low-income and the bottom quintile of non-low-income students for in person learning or post-WN20. Panel B shows the main effects of distance learning, hybrid learning, post-WN20, and first-generation status and interaction effects comparing the variation in outcomes between the bottom quintile of first-generation and non-first-generation students for either distance learning, hybrid learning, or pre-WN20 with that between the bottom quintile of first-generation and the bottom quintile of non-first-generation students for in person learning or post-WN20. Both regressions are expected shortfall regression for the lower quintile and control for additional student, class, and term specific variables. A two-sided one-sample Z-test was used to determine the p-value and no adjustments were made for multiple comparisons.

11 Figure Legends/Captions (for main text figures)

Table 2: Summary of students in all courses, STEM courses, and in a general physics course

			Physics Sections		
	All	STEM	All	Standard	FCI
Low-inc (%)	5.03	4.88	4.23	4.09	3.07
First-gen (%)	13.20	12.97	12.61	11.80	10.50
Male (%)	49.49	50.56	65.93	66.52	66.78
Underrep-min (%)	12.22	12.19	14.04	12.53	12.89
No. students	71823	66461	6886	5475	1171

figures/Figure1.pdf

Fig. 1: Learning modality of STEM course sections by semester. Proportion of the number of course sections that are distance, hybrid, or in person each semester from Fall 2016 to Fall 2022. The dotted vertical line indicates the semester the university officially closed due to COVID-19. Full details are in Supplementary Table B7.

figures/Figure2.pdf

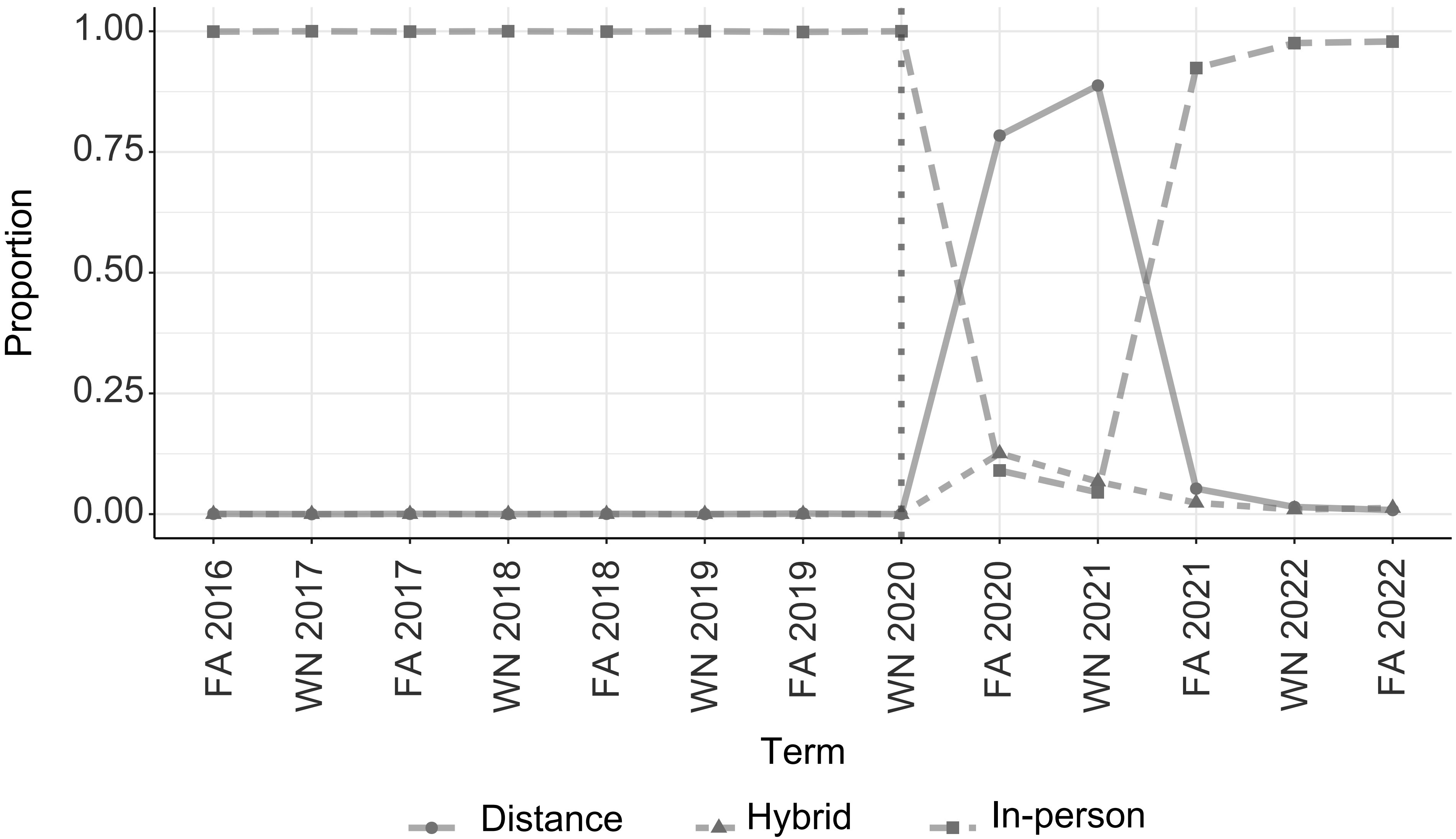
Fig. 2: Association between distance learning and grade outcomes in STEM classes by low-income (low inc) or first-generation (first gen) status. a,b. Data are presented as effect sizes with 95% confidence intervals (error bars) and are estimated through expected shortfall regressions with $\tau = 0.20$ using Model (1), where the dependent variable is the numeric grade outcome ($N = 675,463$). The regression follows the specification in (a) Panel A of Table 1 and (b) Panel B of Table 1. The point shape (triangle) indicates significance at level $\alpha = 0.05$ and the dashed vertical line indicates effect size equal to zero.

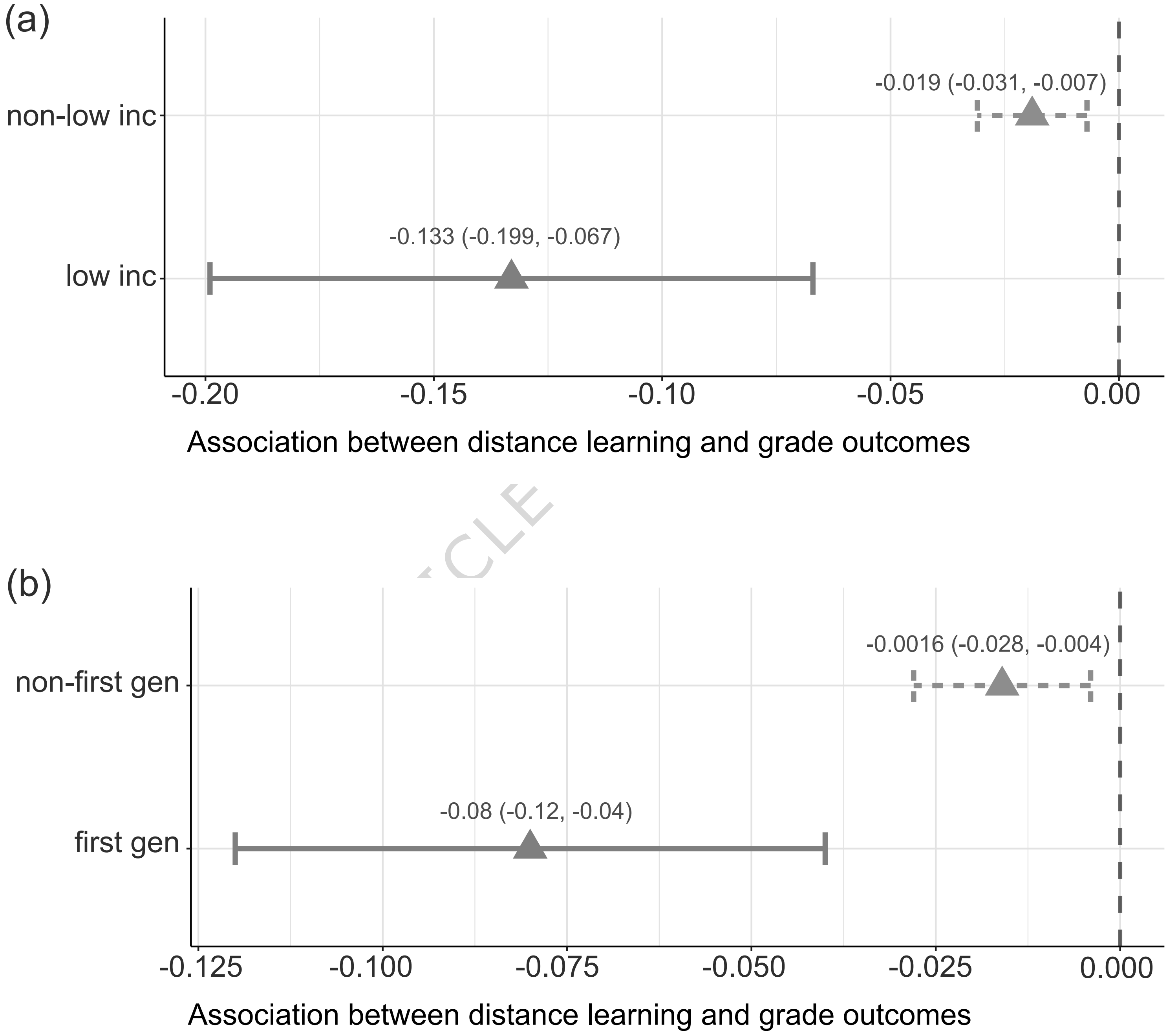
figures/Figure3.pdf

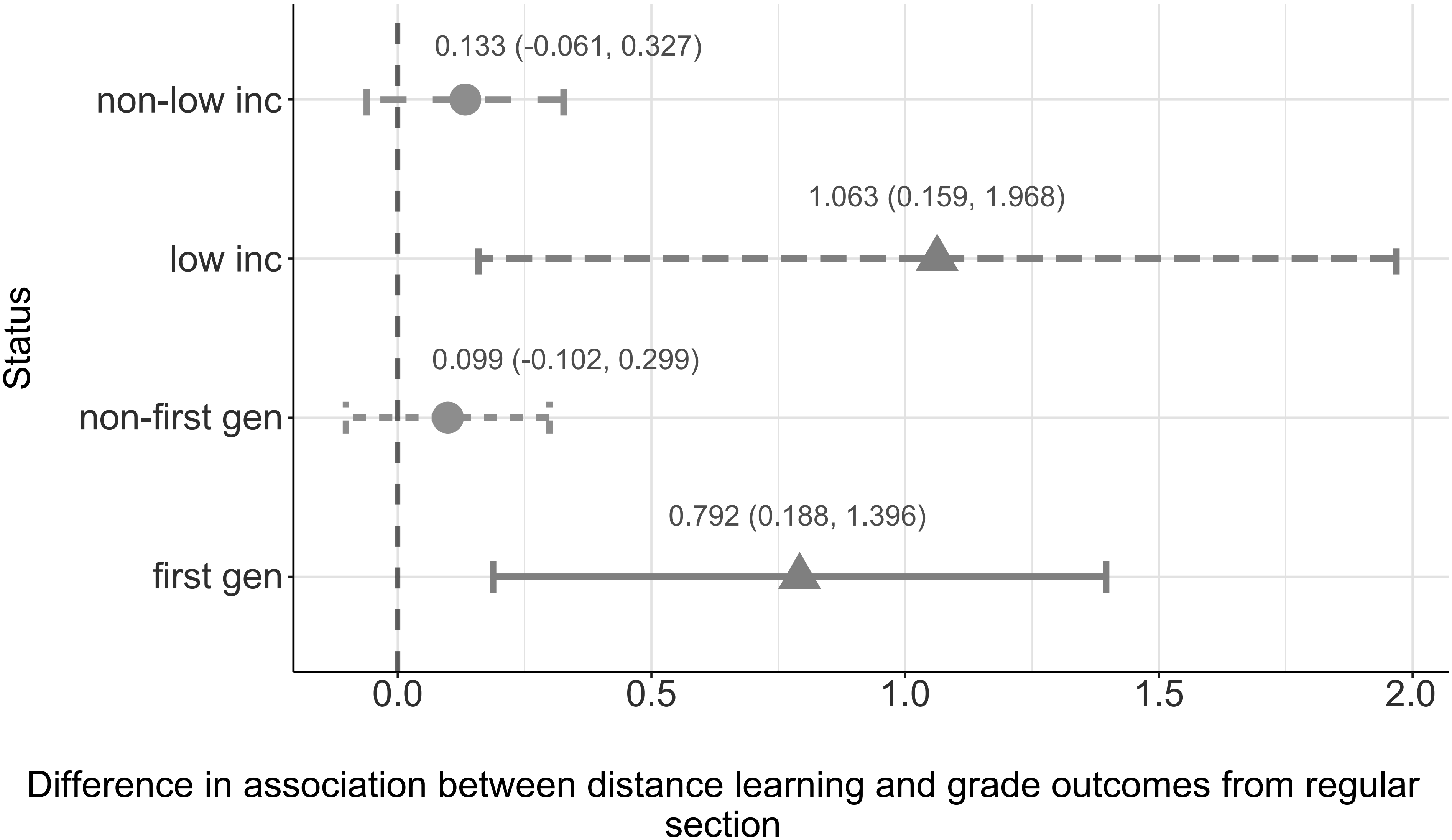
Fig. 3: Association between distance learning, low-income or first-generation status, and grade outcomes in all classes. a,b. Data are presented as effect sizes with 95% confidence intervals (error bars) and are estimated through expected shortfall regressions with $\tau = 0.20$ using Model (1), where the dependent variable is the numeric grade outcome ($N = 366,840$ for Physical and Natural Sciences, $N = 262,202$ for Engineering, $N = 339,341$ for Social Sciences, $N = 75,524$ for Medicine and Health, and $N = 327,673$ for Humanities, Arts, and Languages). Refer to Table B10 for detailed estimates.

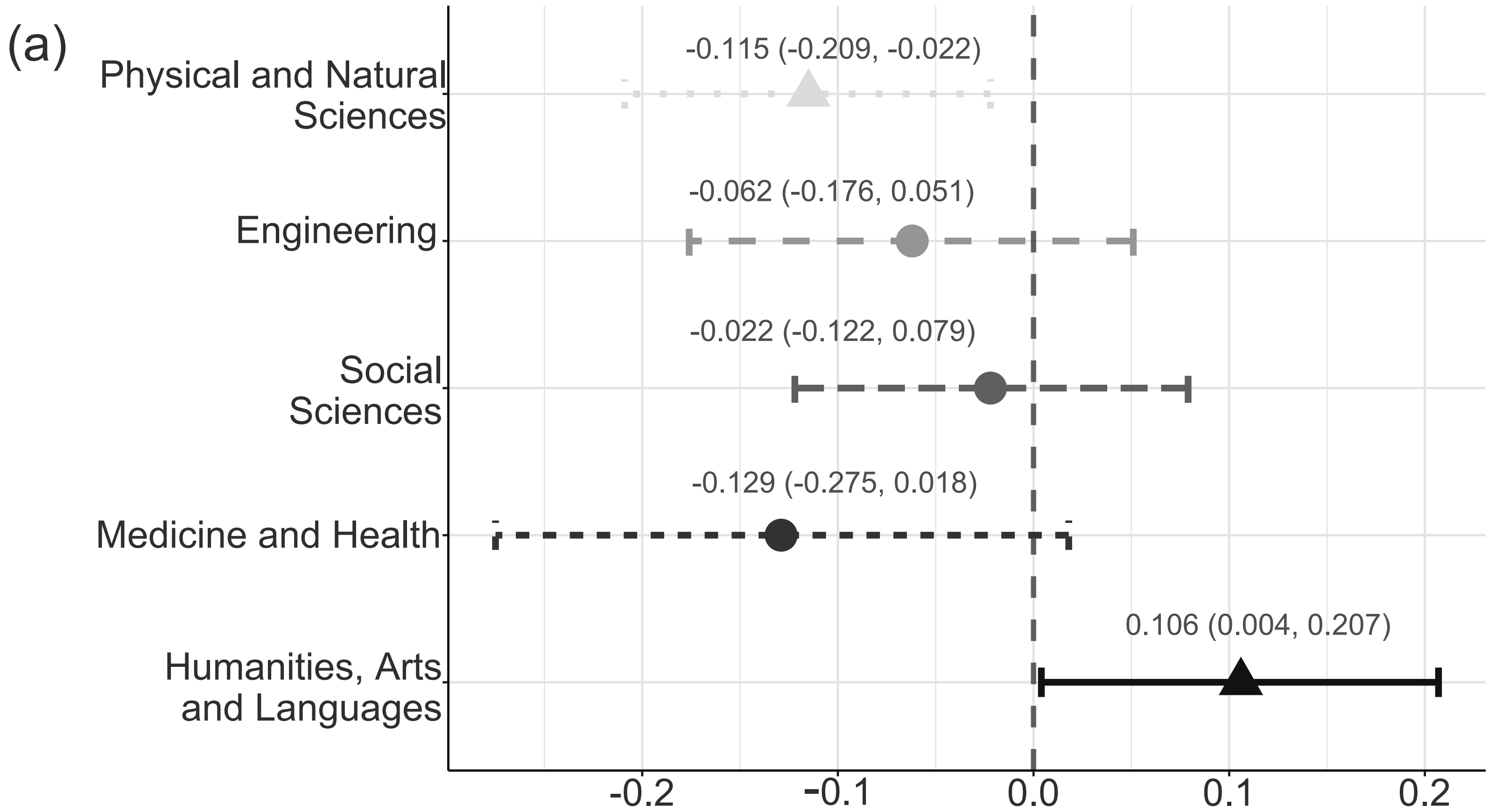
figures/Figure4.pdf

Fig. 4: Difference in association between distance learning and grade outcomes from regular sections to FCI sections of a general physics course by low-income (low inc) or first-generation (first gen) status. Data are presented as effect sizes with 95% confidence intervals (error bars) and are estimated through $\tau = 0.20$ expected shortfall regressions using the Model (2), where the dependence variable is the numeric grade outcome ($N = 7,373$). A positive effect size indicates a less negative association between distance learning and grade outcomes for the FCI section group than its regular section counterpart. The regression follows the specification in column 1 and 3 of Supplementary Table 11.

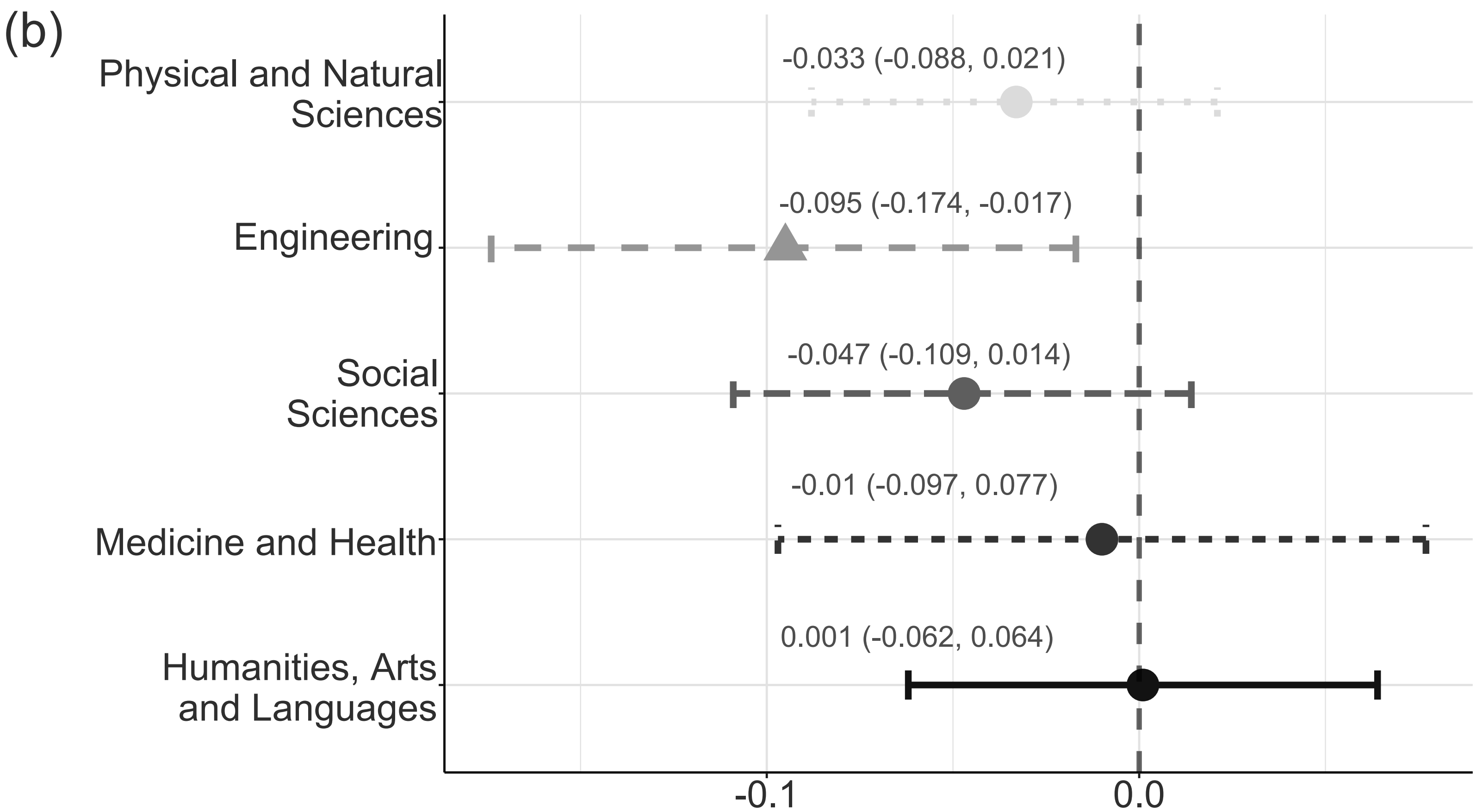

1.00
0.75
0.50
0.25
0.00
Proportion
FA 2016
WN 2017
FA 2017
WN 2018
FA 2018
WN 2019
FA 2019
WN 2020
FA 2020
WN 2021
FA 2021
WN 2022
FA 2022
Term
Distance
Hybrid
In-person


(a)
non-low inc
low inc
-0.019 (-0.031, -0.007)
-0.133 (-0.199, -0.067)
-0.20
-0.15
-0.10
-0.05
0.00
Association between distance learning and grade outcomes
(b)
non-first gen
first gen
-0.0016 (-0.028, -0.004)
-0.08 (-0.12, -0.04)
-0.125
-0.100
-0.075
-0.050
-0.025
0.000
Association between distance learning and grade outcomes


0.133 (-0.061, 0.327)
1.063 (0.159, 1.968)
0.099 (-0.102, 0.299)
0.792 (0.188, 1.396)
non-low inc
low inc
non-first gen
first gen
Status
0.0
0.5
1.0
1.5
2.0
Difference in association between distance learning and grade outcomes from regular section



Additional association between distance learning and grade outcomes for low-income



Additional association between distance learning and grade outcomes for first-generation