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Online Student Performance Under Synchronous and Asynchronous Instruction in California Community Colleges

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Abstract
The COVID-19 pandemic ushered in both an increased use of online courses in general and an increased the use of newer forms of online instruction like synchronous instruction. These changes create an urgent need for updated research on how students perform in these courses relative to face-to-face alternatives. Our paper uses data on student course enrollments in the California Community Colleges system from 2015–16 through 2021–22 to explore how the relative performance of students in asynchronous and synchronous courses compared to face-to-face courses has changed over time and how performance differs across various student subgroups (e.g., by race/ethnicity and financial aid use). While there are still performance gaps between online and face-to-face students post-pandemic, those gaps are smaller than they were pre-pandemic. Moreover, as of 2021–22, course passing gaps compared to face-to-face students are smaller for students in synchronous courses than in asynchronous courses. Trends in performance gaps are more pronounced among specific student groups, particularly Hispanic and Black students, highlighting potential equity concerns tied to course modality choices and the need for targeted interventions to address these disparities.

Keywords Online education · Community colleges · Asynchronous education · Synchronous education · Postsecondary education.

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Introduction

The use of online courses in postsecondary institutions was growing rapidly prior to the emergence of COVID-19 (Ortagus, 2017), and this growth was accelerated during the pandemic (Felson & Adamczyk, 2021). In addition to pushing more courses online, the pandemic also triggered significant changes in the characteristics and formats of online courses available. One notable change was the widespread adoption of synchronous courses, which feature real-time interaction between students and instructors using platforms like Zoom. While the initial adoption of synchronous online instruction was largely unplanned, implemented as an emergency response to the pandemic, this new delivery format was subsequently integrated into many colleges' instructional offerings after the pandemic, opening the possibility to significantly change the post-pandemic online education landscape (Hart et al., 2025a; Libasin et al., 2021; Shlomo & Rosenberg-Kima, 2024; Zeng & Luo, 2023). However, only a modest body of research has examined the academic performance outcomes associated with synchronous online course formats compared with either in-person delivery or asynchronous online delivery.

Understanding the relative effectiveness of synchronous and asynchronous online instruction compared to face-to-face instruction is key for educational institutions and policymakers as they chart the course for post-pandemic education. Such work can not only inform pedagogical decisions, but can also aid in optimizing resource allocation, shaping instructional strategies, and ensuring equitable access to quality education, ultimately contributing to the enhancement of the overall educational experience and outcomes for a diverse range of students. To fill this research gap, this study uses multiple years of administrative data from the California Community Colleges (CCC) system—the largest system of postsecondary education in the United States, boasting 116 colleges and more than 2 million students—to address important questions around how the prevalence of synchronous, asynchronous, and face-to-face course delivery modalities has evolved over time, and how student performance compares across these delivery modalities, particularly since the onset of the pandemic.

Specifically, we consider the following research questions:

(1) How have enrollment patterns in different course modalities, including asynchronous, synchronous, and face-to-face courses, changed over time in a large state community college system?
(2) How do students perform in asynchronous and synchronous courses compared to face-to-face modalities, and how have any performance gaps changed over time?
(3) How do enrollment and performance gaps across different instructional modalities compare for different student subgroups, including sex, race/ethnicity, age, and financial aid status?

We find that enrollment in online courses showed steady growth before the pandemic, but experienced a substantial surge during the pandemic. Online courses accounted for approximately two-thirds of enrollments in the CCC system in 2020–21 and 2021–22. However, given the marked preference for asynchronous versus synchronous courses pre-pandemic, the expansion of synchronous instruction was especially notable. We further find that performance gaps between online courses (both synchronous and asynchronous) and traditional face-to-face courses have decreased over time, with a steeper decrease for the synchronous/face-to-face gap. As of the 2021–22 academic year, synchronous students were 3.1 percentage points less likely to pass their courses compared to face-to-face students; the equivalent gap for asynchronous vs. face-to-face students was 5.8 percentage points. Additionally, trends in performance gaps were more pronounced among specific student groups, particularly Hispanic and Black students, highlighting potential equity concerns tied to course modality choices and the need for targeted interventions to address these disparities. A particular contribution of our study is our ability to address these questions in a large community college system, encompassing a diverse student body and diverse set of course types. These findings provide important new evidence that college systems can use to consider the optimal mix of courses to offer post-COVID.

Literature Review

Challenges and Affordances in Online Learning

In the field of learning sciences, scholars have identified several unique advantages and challenges associated with asynchronous online instruction. With respect to advantages, asynchronous online learning can be more flexible than in-person instruction, allowing students the opportunity to take coursework while balancing work and family obligations (Jaggars, 2014; Hill, 2019). Online learning may also allow for early warning system that identifies at-risk students in a timely way (e.g. Bird et al., 2025). In addition, online learning may offer more personalized approaches to engaging course materials: for instance, by allowing instructors to offer presentation of course material in multiple formats, such as video and text, allowing students multiple approaches to engagement (Li et al. 2021; Xu & Xu, 2020).

However, the greater degree of student control over the pace of their learning in online instruction may also pose challenges, particularly for those with limited self-directed learning skills (Bambara et al., 2009; Bork & Rucks-Ahidiana, 2013; Doherty, 2006; Guglielmino & Guglielmino, 2003; Nash, 2005; Rovai, 2003). Additionally, instructors in asynchronous courses may grapple with the task of fostering a sense of community due to the absence of real-time student engagement with peers and instructors (Garrison et al., 2003; Richardson et al., 2015). Both challenges may contribute to poorer course outcomes for asynchronous online students compared to peers taking courses face-to-face (Xu & Xu, 2020).

Synchronous online delivery may mitigate these challenges and more closely emulate some of the benefits associated with face-to-face instruction. Consequently, it is plausible that synchronous online classes may exhibit smaller performance decrements than asynchronous classes when compared to face-to-face classes. On the other hand, because it requires signing on at designated times, synchronous instruction may offer less flexibility in allowing students to access course material whenever it is convenient for them (Hart et al., 2025a). Moreover, synchronous learning generally requires a stable internet connection and access to reliable technology, as well as a quiet and distraction-free environment for effective participation and the ability to reliably schedule time to attend classes (Hart et al., 2021b; Hart et al., 2025a). These requirements can pose potential obstacles for students who lack access to reliable internet or who have unpredictable schedules, underscoring issues related to the digital divide and equitable engagement in synchronous learning. For instance, Hart et al. (2021a) found that that during the pandemic, students from low-income households were disproportionately disadvantaged due to unreliable internet connections and lack of quiet study spaces. Given the ongoing transformation of digital learning in higher education, it becomes crucial to empirically assess the relative effectiveness of synchronous instruction in comparison to other modalities to inform educational practices and policies.

Prior Evidence on Performance Gaps in Online Learning

A growing body of literature has examined performance gaps in online learning, with most focusing on asynchronous learning. Many of these studies—including several high-quality randomized control trials—have looked at four-year institutions, generally finding null to negative effects of online course-taking (Altindag et al., Forthcoming; Bettinger et al., 2017; Figlio et al., 2013; Kofoed et al., 2024; Krieg & Henson, 2016; see Xu & Xu, 2020, for a review). However, the set of studies most relevant to the present paper focus on online instruction at community colleges.

Performance gaps may plausibly differ across institutional settings since students at two-year colleges are more likely to be employed, attend school part-time, and have caregiving responsibilities; these factors are also all positively associated with online course-taking (Radford et al., 2015). To the extent that there is heterogeneity in course performance gaps associated with characteristics disproportionately represented in community colleges, evidence from the four-year sector may not generalize well to two-year colleges that serve different populations. Online course-taking is also more prevalent at two-year colleges than four-year institutions (Radford), which has prompted a particular investment in online course quality in the community college sector (described further below). Both factors make it important to specifically study online course-taking in community college settings.

The existing body of work in two-year institutions generally indicates that key student outcomes—like course passing and future course-taking—tend to be poorer in online courses compared to in face-to-face modalities (Hart et al., 2018; Huntington-Klein et al., 2017; Johnson & Cuellar-Mejia, 2014; Xu & Jaggars, 2011, 2013; see Xu & Xu, 2019; Sublett, 2019a) for reviews of this literature). [1] Particularly pertinent to this study are articles focused specifically on the California Community Colleges system (Hart et al., 2018; Johnson & Cuellar Mejia, 2014; Palacios & Wood, 2016). Using aggregate data at the college level on outcomes by modality for men of different race/ethnic subgroups, Palacios and Wood (2016) document that course completion and course passing were higher in face-to-face course sessions than in online course sessions, regardless of online modality type, for all subgroups. Johnson & Cuellar Mejia (2014) and Hart et al. (2018) extend these results—and find similar advantages for in-person classes on student course outcomes—using individual-level data with various fixed effect strategies to control for sorting into

[1] [1]A distinct but related literature looking at how online course-taking affects longer-term outcomes (e.g., transfer, time to completion, and degree attainment) finds more mixed results for online courses, with some studies showing null or negative results (Jaggars & Xu, 2010) and others positive results (Johnson & Cuellar Mejia, 2014; Sublett, 2019b; Shea & Bidjerano, 2014; Shea & Bidjerano, 2016). See Xu & Xu, (2019) and Sublett (2019a) for reviews on these questions.

online courses based on course and individual characteristics. These results suggest that while asynchronous online courses offer flexibility and increased access, they may hinder course success as well. However, these studies were conducted prior to pandemic and many of them drew on data from a decade ago or more.

With the increasing prevalence of online instruction and significant transformations in online education during the pandemic (Hart et al., 2025a; Kurlaender et al., 2024), it is plausible that the effectiveness of asynchronous instruction has evolved over time, leading to significant changes in performance disparities between asynchronous and face-to-face classes compared to the pre-pandemic landscape (Altindag et al., Forthcoming). The CCC system, for example, had already made systemwide investments in online education resources before the pandemic. A particularly visible effort was the California Virtual Campus–Online Education Initiative (California Virtual Campus, 2024), which offered colleges access to a shared learning management system (Canvas), faculty training resources, and services like virtual advising and tutoring for online students. Yet, these online education resources and student support services further expanded during the pandemic across the CCC (Hart et al., 2021b). Many colleges expanded professional development training to support instructors newly teaching online (Hart et al., 2021b).

Institutions also scaled up student-facing supports, such as by adding or expanding virtual academic counseling, providing students with access to technology such as laptops or hotspots, and implementing new communication and case management tools to better track and assist students (Hart et al. 2021b; Hart et al., 2025a). These changes reflect a broader evolution toward a more intentional and institutionally-supported approach to online instruction, fundamentally reshaping the infrastructure of online education in ways that have persisted beyond the pandemic. Given the new institutional environment, it is increasingly pertinent to use recent data to provide up-to-date analysis of the effectiveness of asynchronous online instruction relative to face-to-face delivery.

Building a base of knowledge on synchronous online course-taking is also important, as little was known about its effects prior to the pandemic. Some of the best evidence on synchronous course use comes from a randomized controlled study at West Point during the pandemic, which found that students randomly assigned to synchronous online versions of courses had lower course grades than those assigned to face-to-face sections (Kofoed et al., 2024). Students in synchronous online classes reported poorer concentration on course material and less connection to students and peers (Kofoed et al., 2024). Yet, this work was conducted in a selective, highly structured environment. By contrast, examining performance in synchronous online courses within an open-access context represents a major contribution of the present study.

In addition to looking at the evolution of online versus face-to-face performance gaps over time and separating out asynchronous versus asynchronous courses, another contribution of our study lies in comparing performance across modalities for different key student subgroups. Looking across different student subgroups is important because prior research indicates that asynchronous online delivery format tends to be more popular among female students, students of color, and students from lower-income backgrounds, partly because the format offers greater flexibility for students to balance school with work or family responsibilities (Xu & Jaggars, 2014; Jaggars & Bailey, 2010; Johnson & Cuellar Mejia, 2014). However, some of these same groups have also been found to experience larger performance gaps in asynchronous courses compared to their peers (e.g., Xu & Jaggars, 2014, Hart et al., 2018), possibly due to differences in access to technology, quiet study spaces, or self-directed learning skills. These challenges are likely to remain in the post-pandemic periods. By exploring the extent to which the online performance gaps vary across subgroups, our study helps to shed light on the extent to which use of online courses may differentially contribute to student success.

Methods

Data

We draw on student-course level data from the California Community Colleges Chancellor's Office to explore how student performance varies across different instructional formats from 2015–16 through 2021–22. We refer to academic years by the year of the fall term, so 2021 pertains to the 2021–22 academic year. We focus on fall and spring terms, and many of our analyses focus on three specific years—2015, 2018, and 2021. These years were chosen to track trends in course enrollment and performance over time, while avoiding a focus on the years most heavily affected by the COVID-19 pandemic, (2019–20 and 2020–21), when the data on course classifications are less clean and course outcomes may reflect pandemic-era stresses and challenges that may differentially affect intended-face-to-face vs. intended-online students (Hart et al., 2025b; Bacher-Hicks & Goodman, 2021; Bird et al., 2022; Bulman & Fairlie, 2022).

We impose several sample restrictions. We exclude student-by-course level data on enrollments in non-credit courses [2] as well as a small number (< 1% of observations) of student-course observations with excessively high numbers of units attached (> 6 units). We exclude a small number of student-course enrollments where students earned non-standard grades (e.g., special military withdrawals), and courses that are taught in modes other than face-to-face, asynchronous, or synchronous instruction (e.g., mail correspondence courses).

In addition to these restrictions, which focus on data quality needed to enact our analytic strategies, we also make a few additional sample restrictions to focus on groups of particular interest to policymakers: students aiming to use community colleges to pursue goals of transfer or degree receipt. To this end, we drop students without prior high-school credentials, those with prior post-secondary degrees, and students who report academic goals other than transfer or receiving an associate degree (~ 38% of student-course observations). Appendix Table 2 traces how our student sample changes as these and subsequent sample restrictions are added. In robustness tests discussed in Appendix B, we show that our results are not sensitive to including these observations.

We also drop course enrollments in "interdisciplinary" courses (e.g., tutoring sections, counseling sections, college success courses, etc.), which often are not graded (~ 3% of student-course observations). Again, robustness tests (Appendix B) show that our results are not sensitive to including these observations.

[2] Non-credit courses include those not intended to contribute to a degree, such as English as a second language courses, citizenship courses for immigrants, parenting courses, courses intended to remediate primary and secondary-school-level work, etc. (CCCCO, 2025). These constitute less than 15% of the total observations during our sample time period.

A handful of colleges reported exclusively using synchronous instruction in online courses pre-COVID. Yet, as explained further in Appendix B, details from both state reports and from interviews with distance education leaders suggest that these courses likely did not feature the Zoom-based form of synchronous instruction that emerged in the wake of the pandemic. Accordingly, we excluded these colleges from our main analysis. However, we show in robustness tests (see details in Appendix B) that our results are similar when we include these colleges. Enacting these sample restrictions yields a sample of roughly 29 million enrollment records (see Column 5 in Appendix Table 2). We use this sample for our descriptive analyses of course enrollment patterns over time.

However, given that the primary goal of our study is to compare student performance between course delivery formats, our main *regression-based* analyses impose a few additional restrictions. In particular, we further restrict the sample to courses offered both face-to-face and through at least one online modality during our study window, a restriction that eliminates about 16% of observations.

Finally, the main regression-based analyses in our paper draw on data from student-course enrollments during the 2015, 2018, and 2021 academic years. We impose this restriction because most institutions adopted emergency remote instruction—i.e., abrupt transitions to remote instruction rather than offering courses that had been planned as online courses—during the early period of the pandemic; emergency remote instruction is meaningfully different from well-planned and executed online learning (Digital Learning Collaborative, 2022). We therefore exclude the 2019–20 and 2020–21 academic years from our regression sample and focus on the 2021–22 year as our post-pandemic reference point when college had resumed more stable instructional operations.[3] We similarly drop 2016–17 and 2017–18 so as to trace the transition of online learning outcomes at three-year intervals throughout our regression sample.

After restricting to those three years, our main analytic sample in our regressions includes nearly 10 million student-course enrollments (see column 7 in Appendix Table 2), representing 112 campuses. Appendix Table 3 traces how the student and modality characteristics differ across years. As expected, the modalities used change substantially over time—especially in 2021 compared to earlier years—while student characteristics remain more stable.

Measures

Our primary outcome measure assesses whether students successfully pass a course, defined as earning a grade of C or better or receiving a Pass designation in Pass/No-Pass classes.

Our main predictors of interest capture course modes. Some courses include multiple instructional components, such as a lecture component and a lab component. We characterize courses with at least one asynchronous component as asynchronous; courses with at least one synchronous component (but no asynchronous component) as synchronous; and

[3] While there were still some COVID-related disruptions as of the 2021–22 academic year, as new virus variants resulted in a surge of COVID cases and sometimes prompted course sessions to shift online, the CCC Chancellor's Office provided guidance to try to improve accuracy of reporting of course modalities compared to prior periods—e.g., spring 2020—where classes were abruptly transitioned online (California Community Colleges Chancellor's Office, 2022).

courses with all components face-to-face as face-to-face. In practice, the vast majority of courses either consist of only a single component or are taught in the same mode for all components. Courses with multiple modalities account for less than 3% of our analytic sample. However, in robustness checks (Appendix B), we show that our results are not sensitive to different ways of treating courses with components taught in different modes.

We employ several section-level controls. These include the number of students in the section, as well as section-level measures capturing the share of peers ever recorded with an exceptionality (i.e., disability); the share of peers intending to earn an associates degree or transfer (vs. reporting academic goals that are neither degree- nor transfer-oriented); and the share of peers receiving need-based financial aid. Peer measures are constructed using leave-one-out averages of section characteristics; that is, they are constructed excluding data from each focal student in turn. Given evidence in prior work of peer effects in student outcomes (e.g., Carrell et al., 2009), these measures account for the possibility that peer composition may differ in face-to-face vs. online sections of courses. However, in specifications available on request, we confirm that our results are not sensitive to inclusion of these controls.

Because we expect that student, course, and college characteristics might be associated both with course modalities and student outcomes, we include fixed effects at these levels, as we describe below, to account for characteristics that are invariant across those units.

We also use sex, race, age, and financial aid variables to stratify our sample and look for differences in patterns across student subgroups. Specifically, we explore how results differ for males versus females; for students across five race groups (Hispanic, White, Asian, Black, and "other race"); for older (age 25+) vs. younger students; and for students using need-based aid vs. not using need-based aid.

Models

For our analyses of course modalities over time, we produce simple descriptive stacked bar graphs displaying the share of enrollments taken through synchronous and asynchronous course modalities over time from the 2015–16 academic year to the 2021–22 academic year, focusing on fall and spring terms. We drop summer terms and—for schools on the quarter system—winter terms. While our regression analyses focus only on courses that are offered in multiple modalities and in three specific years (as described above), these descriptive analyses draw on the broader range of courses that include those offered only in single modes in order to gain the most accurate representation of the overall course-taking patterns. Similarly, for our analysis of student characteristics by course modes, we produce simple descriptive stacked bar graphs looking at the share of students in different groups stratified by course modes. For instance, we look at whether female students are differentially represented in face-to-face vs. synchronous vs. asynchronous course modes.

To compare performance outcomes in different course modes, we use linear probability models with a saturated set of fixed effects. One methodological challenge to credibly estimating the relationship between course delivery mode and student performance is that the likelihood of online course *offerings* may be correlated with college, course, or time characteristics that are tied to pass rates. For instance, if math courses are less commonly offered online (synchronously or asynchronously) than English courses, and the latter tend to have higher pass rates, it could introduce bias into our estimates if we did not account for systematic differences across departments. In order to provide estimates that account for differences in modality offerings across colleges, courses, and time, we employ college-course-term fixed effects. This means that we only compare performance outcomes among students taking the same course (e.g., Bio 101) in the same college (e.g., College of Marin) during the same term (e.g., fall 2019).

However, even after including college-course-term fixed effects, there may be remaining bias if students systematically sort into sections taught through different modalities within a specific course. If, for instance, students with heavy family obligations are more likely to opt into asynchronous delivery to fit with their schedules, and less likely to pass courses due to competing demands, the estimates of online course modes on student outcomes would be biased downwards. Indeed, descriptive statistics for our sample (Appendix Table 4) show that students age 25 and over—who may be more likely than younger students to have work and family obligations—are disproportionately likely to be in online classes, suggesting that such concerns may be valid.

To address sorting of students to different modalities within courses, we augment our model with a second set of fixed effects, incorporating student-term fixed effects along with our existing college-course-term fixed effects. As a result, any within-individual differences that remain constant within a particular semester (e.g., family obligations) are accounted for by these additional fixed effects. In addition, since we cannot include section fixed effects because our course modality variables are defined at the section level, we control for section-level characteristics like course section class size.

While the inclusion of this saturated set of fixed effects minimizes bias from sorting, it introduces concerns about the generalizability of our results since our effects are estimated from units that have variability in modality at either the college-course-term and individual-term levels. As we show in appendix tables, the characteristics of college-course-term and student-terms that are observed in multiple modes are in many cases similar to those that are observed only in single modes. However, courses in certain subjects (e.g., humanities and social science in both 2015 and 2021, math in 2021) are more likely to be observed in multiple modes in the same term (Appendix Table 5). Similarly, certain student types were more likely to be observed in multiple modes in the same term, although this differed by years (Appendix Table 6). For instance, older students were over-represented among single-mode students in 2021 but were (narrowly) under-represented among students observed in only one mode in a given term in 2015. These limitations should be kept in mind when considering external validity.

We estimate models relating course passing (receiving a grade of C or higher or a pass designation, $Pass_{ijcst}$) for student i enrolled in section j of course c at college s in term t to course modalities (synchronous [$Synch_{jcst}$] or asynchronous [$Asynch_{jcst}$], with face-to-face courses [FtF] serving as the omitted category), controlling for course-college-term fixed effects (θ_{cst}), student-term fixed effects (μ_{it}), and section characteristics (Sec_{jcst}):

$$Pass_{ijcst} = \beta Asynch_{jcst} + \delta Synch_{jcst} + \sigma Sec_{jcst} + \mu_{it} + \theta_{cst} + \varepsilon_{ijcst} \quad (1)$$

Because we use college-course-term and student-term fixed effects to control for both observed and unobserved variation at those levels, college, course, student, or term level controls would be automatically dropped from the model due to collinearity and we do not include controls at those levels in our equations. The term ε_{ijcst} represents an independently and identically distributed error term, and standard errors are clustered at the college-course level. While we run these models for each focal year (2015, 2018, and 2021) separately, in robustness checks in Appendix B, we show that our conclusions are very similar if we run models pooling all years including mode-by-year interaction terms instead.

Because our data is drawn from administrative records and our main covariates are generated based on peer characteristics, there is virtually no missingness for covariates in our main regressions (<0.05% of records). We include missing variable dummies to preserve other information for these few records. We discuss how we address limited missingness in other covariates that applies to our robustness tests in Appendix B. Similarly, grading records are very complete. This gives us greater confidence in the fidelity of our models.

While our saturated models are designed to account for many potential sources of bias in our estimates, we also conducted direct tests to assess student sorting (see Appendix B, Tables 7-8). Taken together, the patterns of selection that we observe into online courses suggest that some of our key results may actually be conservative estimates if student sorting is not fully accounted for in the model. Specifically, we predict students' likelihood of passing courses based on student pre-course characteristics (such as financial aid use and basic skill course-taking) using college-course-term fixed effect models. We find that students who enroll in online sections tend to have, if anything, a higher predicted "propensity to pass" compared to their peers who opt for face-to-face sections.

Similarly, we estimate course difficulty by calculating a course passing rate for face-to-face course sections as of 2019 and use student-term fixed effects models to explore whether students take more difficult courses online than face-to-face. We find that if anything, the courses that students take courses asynchronously post-pandemic have higher pass rates, relative to the courses those same students take face-to-face and synchronously. This suggests that any decrements in performance in asynchronous courses in post-pandemic terms relative to other formats is unlikely to be due to students sorting into harder classes asynchronously. Again, while these results give a sense of the overall direction of bias in uncontrolled comparisons, our models' inclusion of fixed effects capturing both course and student characteristics ensure that the results presented below are purged of such bias.

Results

Course-Taking Pattern Results

The number of enrollments in online courses had been growing steadily prior to the pandemic, rising from about 15% of enrollments in 2015–16 to 21% in 2018–19, the last academic year unaffected by the pandemic (Fig. 1). The growth of online courses substantially accelerated as a result of the pandemic, rising to represent about two-thirds of enrollments in 2020–21 and 2021–22 (Fig. 1).

Asynchronous instruction dominated online course offerings throughout the entire study period. Synchronous instruction, though still a small proportion of enrollment, grew particularly quickly following the pandemic, increasing from less than 1% of enrollments

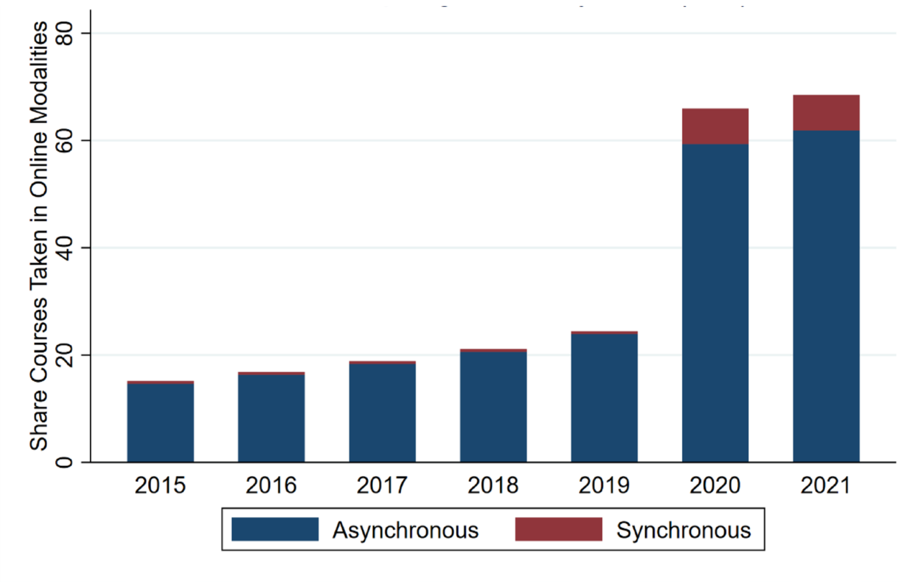

Fig. 1 Share of Courses Taken in Online Modalities, Fall and Spring Terms by Year. *Note* Authors' calculations from California Community Colleges Chancellor's Office Data. Years refer to year during fall term

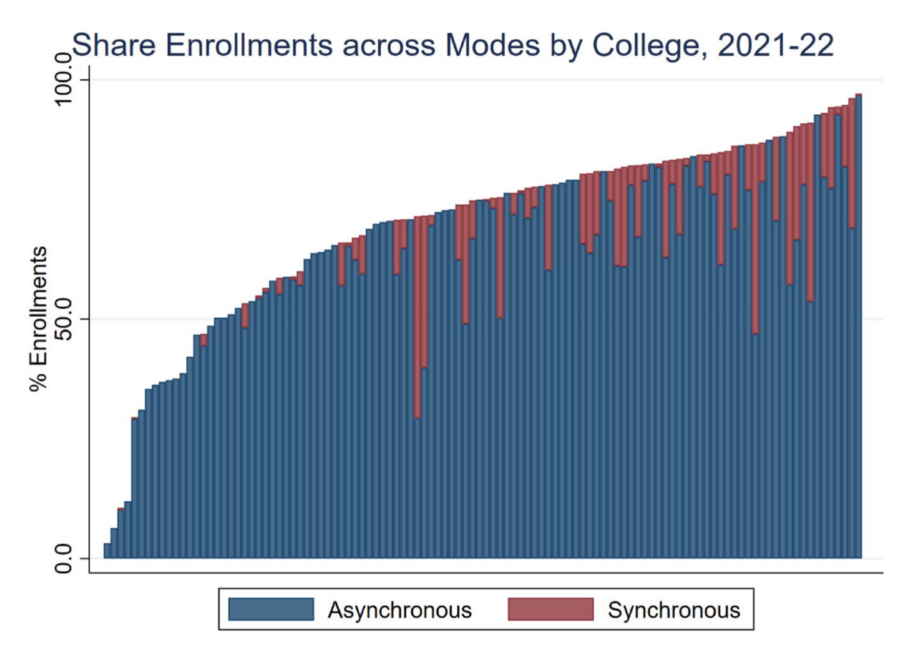

Fig. 2 Distribution of Synchronous and Asynchronous Enrollments by College, 2021–22. *Note*: Authors' calculations from California Community Colleges Chancellor's Office Data

pre-pandemic to roughly 7% of total enrollments in 2021–22.[4] The use of different online course types is not evenly distributed across colleges (Fig. 2); many colleges (around 43%) still reported using exclusively asynchronous instruction in online courses as of 2021–22. However, most colleges use a mix of both online modes. Similarly, the use of synchronous courses is especially pronounced for particular subjects, such as math (15% of enrollments were taken synchronously in 2021–22) and foreign languages (14% of enrollments synchronous; Fig. 3). For other subjects, like education, the use of synchronous enrollments is quite limited (2% of enrollments synchronous).[5]

Figure 4 provides differences in enrollment demographics by course modality in 2021–22, the most recent year for which we have data available. Several notable patterns emerge. For instance, female students are overrepresented in online classes, particularly in asynchronous courses, relative to their share of enrollment in face-to-face classes. Roughly 48% of students in face-to-face classes are females, compared to 53% in synchronous courses and 58% in asynchronous courses. Hispanic students are underrepresented in online classes relative to their representation in face-to-face course enrollments (where they make up 53.9% of enrollments). The opposite is true of White students, who are over-

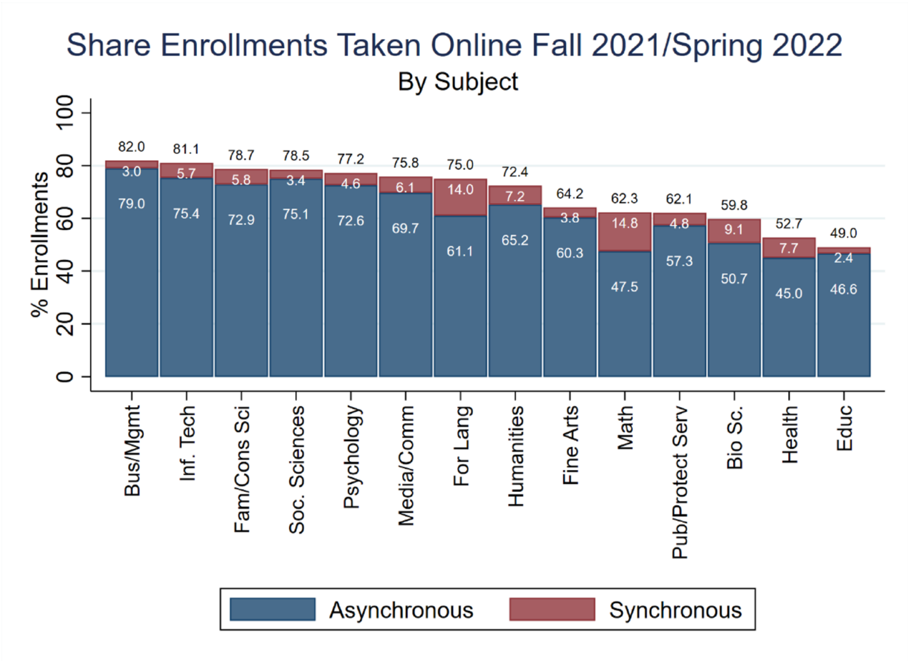

Fig. 3 Share of Courses Taken in Online Modalities, 2021–22, by Course Subject. Note: Authors' calculations from California Community Colleges Chancellor's Office Data

[4] If we include colleges where all pre-pandemic online courses were synchronous, the comparable figures are less than 1.5% of enrollments pre-pandemic synchronous vs. 9% in 2021–22.

[5] Similar figures appear in Appendix Figure 6 for 2015 and 2018. They show that pre-pandemic, information technology and business courses were the subjects most-taken online, with larger gaps when compared to other subjects than are observed in 2021. Synchronous course-taking ranged from 0.2%-1.4% of enrollments across subjects.

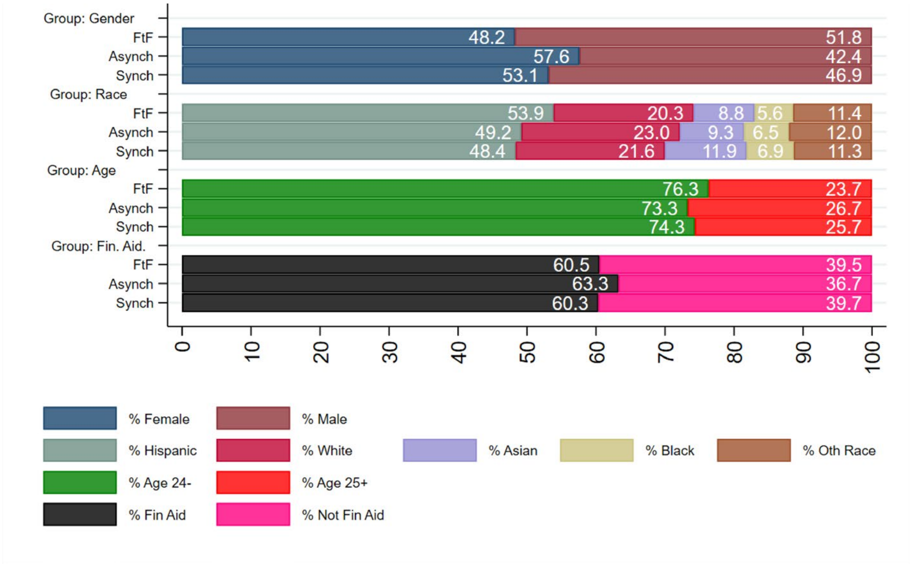

Fig. 4 Race and Sex Characteristics by Mode, Fall 2021/Spring 2022. *Note* Authors' calculations from California Community Colleges Chancellor's Office Data

represented in online classes, particularly asynchronous courses. Asian students—and to a lesser extent, Black students—are overrepresented in online courses, particularly synchronous online classes, relative to face-to-face classes. In terms of age, older students (ages 25+) are over-represented in online courses relative to face-to-face courses, particularly for asynchronous courses. With respect to financial aid use, students receiving need-based aid are somewhat more heavily represented in asynchronous courses than in other modes. Differences in uptake of online courses may have equity implications depending on the extent to which the different course modes are associated with performance gaps.

These differential course-taking patterns suggest that it is important to control for student, subject, college, and term-level factors that may be both correlated with course modality choices and student outcomes. Our models address this concern by using both student-term fixed effects and college-course-term fixed effects to control for sorting into course modalities.

Performance Results

We find that while performance gaps between students in online (both synchronous and asynchronous) and face-to-face classes remain as of the 2021 academic year, they have diminished somewhat over time. Table 1 provides differences in pass rates in 2015, 2018, and 2021 between asynchronous and synchronous courses relative to face-to-face courses, both in raw terms (Panel A), and as estimated by our saturated models that include college-course-term fixed effects and student-term fixed effects (Panel B). Because they address bias due to sorting, we emphasize the estimates in Panel B.

These highly-saturated estimates show that asynchronous/face-to-face performance gaps were shrinking even prior to the pandemic, decreasing from an 8.3 percentage point gap in

Table 1 Main results: pass/A/B/C rates by modality, relative to face-to-face courses

	2015 b/se	2018 b/se	2021 b/se
Panel A. Uncontrolled Models			
Online Asynch	−0.068***	−0.040***	−0.010***
	(0.002)	(0.002)	(0.003)
Online Synch	−0.092***	−0.016	−0.016***
	(0.013)	(0.011)	(0.005)
Outcome Mean: FtF	*[0.678]*	*[0.690]*	*[0.675]*
N	3,496,379	3,628,719	2,844,895
Synch-Asynch (p)	0.07	0.03	0.17
Panel B. Full Models			
Online Asynch	−0.083***	−0.071***	−0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.120***	−0.087***	−0.031***
	(0.012)	(0.009)	(0.003)
Outcome Mean: FtF	*[0.678]*	*[0.690]*	*[0.675]*
N	3,496,379	3,628,719	2,844,895
Synch-Asynch (p)	0.00	0.07	0.00

Source: Author's calculation from CCCCO data. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Coefficient (cluster robust standard error). Standard errors clustered at college-course level. Panel A represents uncontrolled relationships between modalities and course completion. Panel B adds college-course-term fixed effects, student-term fixed effects, and section controls including section class size and section-level leave-one-out averages of the share of students with the following: ever exceptional, intending AA or transfer, on financial aid. College, course, student, and term controls subsumed in fixed effects. Missing dummy variables included for all control variables

course passing rates in 2015 (Column 1) to a 7.1 percentage point gap in 2018 (Column 2). These gaps fell further to 5.8 percentage points in 2021. Estimated synchronous/face-to-face gaps in course passing rates closed even more dramatically during this period, from 12.0 percentage points in 2015 to 8.7 percentage points in 2018 to 3.1 percentage points in 2021. This change may reflect multiple influences; in addition to potential changes in course quality, the fact that so few courses were taken synchronously pre-pandemic may mean that the courses taken online were unique in ways that limit generalizability.[6] While this gives us some pause in interpreting how much the performance gaps between synchronous and face-to-face courses have changed over time, we have more confidence in our estimates for 2021.

That said, the implications for student success in online courses post-pandemic should also be interpreted with some caution, since face-to-face course passing rates in 2021 dropped about 1.5 percentage points between 2018 and 2021 (see italicized row of outcome means in face-to-face courses). This means that while the gaps between online and face-to-face modalities narrowed over time, we do not see clear evidence that the overall likelihood of course passing in asynchronous courses improved over time between 2018 and 2021. On the other hand, the shrinking of performance gaps between 2015 and 2018 for both synchronous and asynchronous courses occurred in the context of rising course passing rates in face-to-face

[6] Appendix Figure 7 shows the number of unique college-course-term cells observed in one, two, or three unique modes within the same term. College-course-terms observed in two or more modes contribute to identification within college-course-term fixed effects in that term.

contexts (69.0% in 2018 vs. 67.8% in 2015), suggesting that the improvements in online student outcomes over the pre-pandemic period occurred in both relative and absolute terms.

To check the sensitivity of our main results, we implement several robustness tests using different versions of the models, different sample exclusions, and different ways of classifying online courses (Appendix B, Appendix Tables 9, 10, 11, 12). For instance, because some recent work has suggested that two-way fixed effects models can be biased, we reduce the dimensionality of our data by implementing our college-course-term fixed effects strategies and student-term fixed effects strategies in turn rather than simultaneously; we find that the pattern of our results is similar though the magnitude is somewhat more modest in less-dimensional FE models (consistent with the less-dimensional models purging our estimates of less sorting bias than our preferred estimates). We also show that our estimates for synchronous and asynchronous course-taking are not sensitive to different ways of classifying course modalities to capture hybrid instruction (i.e., instruction that occurs in different modes in different course sessions, as when a class has asynchronous lectures but face-to-face labs). Finally, we find that our pattern of results is not sensitive to adding schools with all-synchronous online courses back to our sample, or to other sample limitations that we impose in our main specifications. The stability of our results across specifications gives us added confidence that our estimates are accurate.

One possible explanation for the diminished course modality gaps in the post- pandemic period relates to changes in the prior online learning experiences that students brought to bear in their classes. For instance, most first-time-freshmen entering in 2021–22 would have had experience taking online courses in high school during the pandemic, whereas first-time freshmen entering in 2018–19 would have been much less likely to have had such experience. If this is the case, we might expect to see particularly large improvements in online courses post-pandemic for 18- to 20-year olds (roughly the ages of students that might have experienced online high school and been in college in the 2021–2022 academic year). We separated our sample into students 18–20 vs. 21 and over and looked into how gaps in performance changed across years for these groups (Appendix Table 13, Panels B and C). We did not find evidence that performance gaps shrunk more post-pandemic for younger students. Indeed, if anything, shrinkage in performance gaps was more marked for older students.

However, older students post-pandemic might also have had more online experience than older students pre-pandemic if they were forced into online coursework during the spring 2020-spring 2021 terms. To account for this, we ran another set of analyses where we separated first-term students (Panel D) from returning-term students (Panel E), theorizing that first-term students should have been less likely to have gained experience with online learning during the transition to emergency remote instruction. We do see modest evidence that the shrinkage in performance gaps between 2018 and 2021 was larger for the returning-term students for synchronous courses in particular, where the performance gaps in 2018 were very similar to those for first-term students (around $b = 0.088$–0.089) but shrank to -0.029 in 2021 (vs. -0.037 for first-term students). This suggests some role for experience in online course-taking in reducing the performance gaps between online and face-to-face courses post-COVID.

Subgroup Performance Gaps

We also look at subgroup analyses of performance gaps during 2021 specifically (the most recent year of data; Fig. 5; Appendix Table 14 presents these results in tabular form). Models

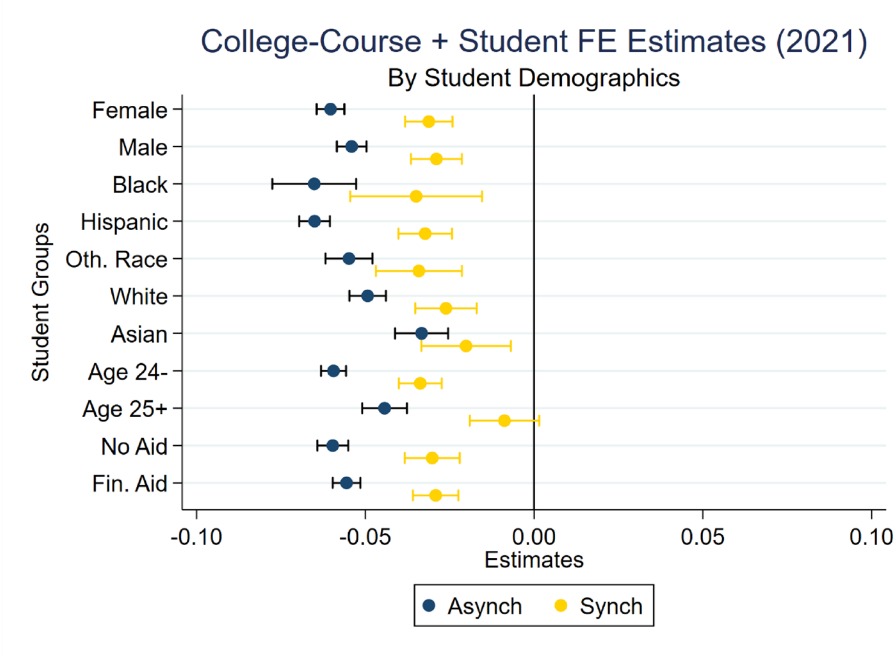

Fig. 5 Course Modality Estimates and 95% Confidence Intervals by Student Demographics: Pass/A/B/C Rates by Modality, Relative to Face-to-Face Courses. College-Course-Term and Student-Term Fixed Effects Estimates, 2021. *Notes* Includes fall 2021 and spring 2022 terms. Models as defined in Table 1, Panel B

are defined as in our main specifications in Table 1, Panel B, with separate regressions run for each student subgroup listed. The points and bars in blue represent estimates of the asynchronous/FtF performance gap, while the points and bars in yellow represent estimates of the synchronous/FtF performance gap.

We observe a pattern of larger asynchronous/FtF gaps than synchronous/FtF gaps that is remarkably consistent across all groups but is especially notable for certain groups. The most pronounced differences are by age. Older students (aged 25+) have smaller online/FtF gaps in both modalities compared to their younger counterparts, but the differences are especially stark for synchronous courses. Older students did not have significantly different success in synchronous courses compared to face-to face courses, whereas their younger counterparts were significantly less successful in synchronous courses than in face-to-face courses.

Similarly, some notable differences appear by race. Asynchronous/FtF and asynchronous/synchronous performance gaps are particularly large for Hispanic and Black students, though relatively imprecise estimates for Black students translate into a slight overlap in confidence intervals for the synchronous and asynchronous estimates. Asian students had the smallest asynchronous/FtF and synchronous/FtF performance gaps. These patterns suggest that performance advantages in synchronous relative to asynchronous courses are widely shared, but that traditionally underserved groups like Black and Hispanic students may especially benefit from greater access to synchronous courses as an online option.

Discussion

While performance decrements associated with asynchronous online education in open-access institutions have been well documented (Xu & Xu, 2019; Sublett, 2019a, 2019b), our study suggests that the student performance gap between asynchronous and face-to-face (FtF) classes may have been narrowing prior to the COVID-19 pandemic. While, on average, the asynchronous/FtF gap narrowed by roughly the same amount during the pandemic as it did in the three years prior, the synchronous/FtF performance gap has decreased more sharply since the nation-wide move to emergency online education. Indeed, post-pandemic, gaps between online and face-to-face success are smaller in synchronous online modalities compared to asynchronous online classes. This is true for all student subgroups that we explored. These results capturing shrinking performance gaps between online and face-to-face classes echo results by Altindag et al. (Forthcoming) in the context of a four-year university setting.

On the other hand, our relatively sanguine results for synchronous courses in 2021–22, with modest performance decrements observed in synchronous online courses, contrast with those found by Kofoed et al. (2024). These divergent results may be driven by both the differences in context (selective four-year military institution vs. community colleges) and time (since their study occurred in fall 2020, when pandemic stressors were more acute and familiarity with online courses may still have been lower). More work should be done to explore how performance differences in synchronous courses continue to evolve and how performance differences vary across settings.

The changes we observe in online student performance could be the result of several factors. Community colleges across California made substantial investments in support for online learning during the pandemic (Hart et al., 2025a; Kurlaender et al., 2024). Investments in broadband access, for instance, may have improved the feasibility of synchronous engagement, while efforts around faculty professional development may have contributed to improved use of technology tools and increased skill and comfort with online content delivery. Similarly, remote-only learning options may have forced many students to quickly improve their online learning skills with increased technical support and resources from their colleges.

The investments made by colleges to improve online learning during the pandemic could lead to improvements in both asynchronous and synchronous classes. However, given the low prevalence of synchronous classes pre-pandemic, the marginal investment necessary to scale up this mode of instruction may have been greater than the investments necessary to scale up delivery of asynchronous courses since the latter were already widely used. In addition, colleges invested effort into developing norms around use of synchronous platforms such as Zoom (Hart et al., 2025a), which may have resulted in improved quality of delivery of synchronous courses during the pandemic.

While we find performance gaps across all subgroups we examined, the pattern of performance gaps across modes may have equity implications for different student subgroups. In particular, the observed over-representation of Hispanic students in face-to-face courses relative to online modalities may be considered positive given that, similar to prior research (e.g., Xu & Jaggars, 2014, Hart et al., 2018; Johnson & Cuellar Mejia, 2014), we find that Hispanic students also have particularly large performance gaps between online and face-to-face classes. The opposite is true for older students. While older students in our sample are overrepresented in online courses, we find that these students have smaller performance gaps than their younger peers, particularly in synchronous courses.

Our findings related to performance differences between synchronous and asynchronous online classes have implications for how schools might consider configuring course offerings to improve equitable outcomes across groups. For example, given that traditionally-underserved groups, like Black and Hispanic students, had particularly large performance gaps between synchronous and asynchronous courses—with more positive results in synchronous courses—colleges may want to consider expanding synchronous course offerings with an eye to equitable outcomes for students who prefer online course modalities to face-to-face options. Expanding synchronous offerings might have especially positive effects for older, returning students with college experience but no degree, a population of particular interest in many states.

Our study has several important limitations. The outcome we focus on–course passing—relies on course grades, which are subjective. This means that standards may not be entirely consistent across courses, across instructors, or over time. Future work on this question should seek to supplement these outcomes with more objective measures.

We also note that there are potential limitations to generalizability over several dimensions. First, we focus on a specific college system, the California Community Colleges. It is possible that results would differ for other state community college systems or at four-year universities. Moreover, our estimation strategy relies on variation within students and courses in order to identify effects. This means that courses and students in our sample that lack such variation in modality are not contributing to the identified effects. If students and courses that lack such variation in modality also had different relationships between online course-taking and course success, our results would not generalize well to those populations. This concern particularly applies to our analysis of synchronous courses in pre-pandemic years, given that fewer courses were taken in this modality pre-pandemic and we therefore have fewer observations contributing to the estimation of effects of synchronous course-taking in those years.

Our study points to several potential avenues for fruitful inquiry. A clear extension is replicating this work to include more recent years, when the impacts of the pandemic have reduced and online education, both synchronous and asynchronous, has matured. Similarly, it would be important to replicate this work in other contexts – in four-year colleges and in different states.

We also call for a deeper examination of the structural, pedagogical, and social features that might explain our results. Examinations of online course shells to explore facets of course quality for asynchronous courses; live observations of synchronous classes; analyses of the effects of instructor professional development; and interviews with faculty, staff, and students could lead to a richer understanding of the mechanisms that explain our results. Of course, such an understanding would allow for more targeted and effective interventions.

While additional research is needed, our results help provide important context to open-access institutions as they consider the optimal mix of face-to-face, asynchronous online, and synchronous online classes post-pandemic. As performance gaps continue to close, colleges may consider increasing online offerings in both modes now that initial pandemic-driven investments have already been made to improve their capacity for synchronous and asynchronous courses.

Appendix A Additional Tables and Figures

See Figs. 6 and 7

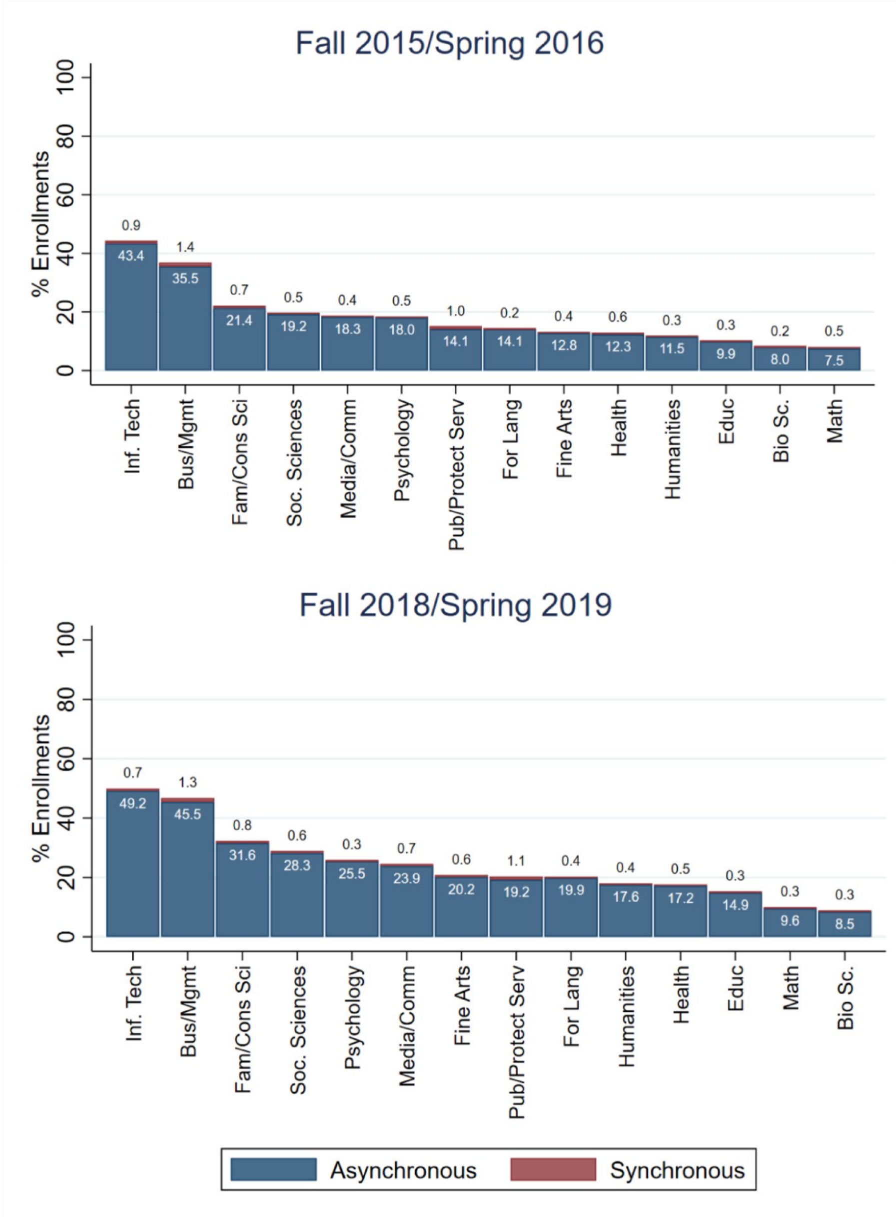

Fig. 6 Share of Courses Taken in Online Modalities Pre-Pandemic, by Course Subject. Note: Authors' calculations from CCCCO Data. Labels for share of synchronous courses are given in black; labels for share of asynchronous courses are given in white

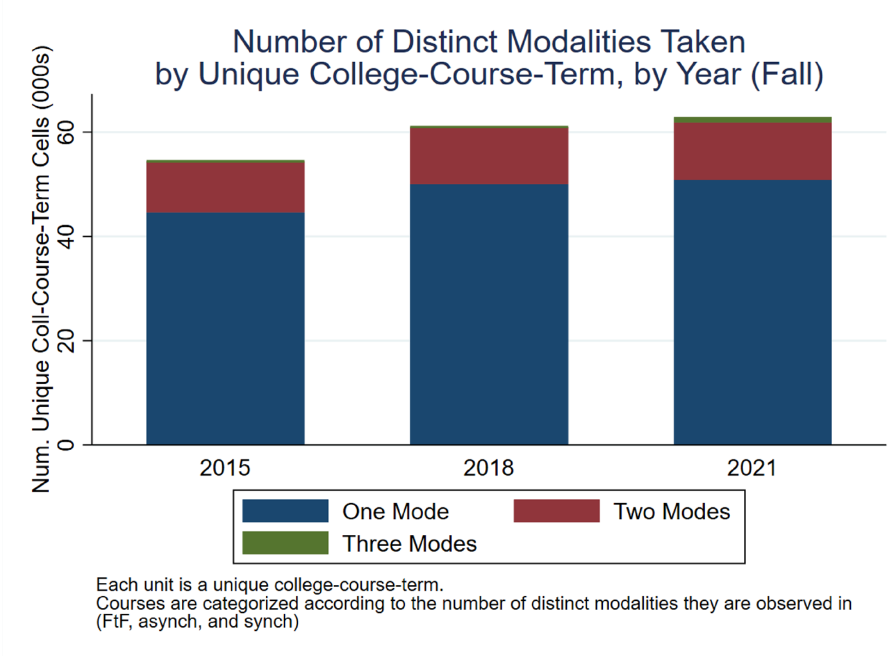

Fig. 7 Number of Distinct Modalities Taken by Unique College-Course-Term, by Year (Fall). Note: Authors' calculations from CCCCO Data. Each unit is a unique college-course-term observation. Courses are characterized according to the number of distinct modalities they are observed in (FtF, asynch, and synch) in a given term

See Table 2, 3, 4, 5, and 6

Table 2 Changes in mean student characteristics as sample exclusions are added

	Add Sample Exclusions Based On:						
	Full Sample (1)	Prior Credential/Ed. Goals (2)	Interdisc (3)	Fall/Spring (4)	All-Synch (5)	Mode Variation (6)	2015, 2018, 2021 (7)
Demographics							
Hispanic	0.47	0.49	0.49	0.49	0.50	0.50	0.50
White	0.25	0.23	0.24	0.24	0.23	0.23	0.23
Asian	0.11	0.10	0.10	0.10	0.10	0.10	0.10
Black	0.06	0.06	0.06	0.06	0.07	0.06	0.06
Other Race	0.11	0.11	0.11	0.11	0.11	0.11	0.11
Female	0.55	0.54	0.54	0.53	0.53	0.54	0.54
Need-Based Aid	0.58	0.63	0.63	0.64	0.64	0.65	0.65
Age 25+	0.31	0.24	0.24	0.24	0.24	0.23	0.23
Has Exceptionality	0.08	0.08	0.08	0.08	0.08	0.08	0.07
Prior Ed. Credentials							
Prior HS Diploma	0.76	0.89	0.90	0.90	0.90	0.90	0.90
No Prior HS Degree	0.06	0.00	0.00	0.00	0.00	0.00	0.00
HS Grad, Foreign Diploma	0.04	0.05	0.05	0.04	0.04	0.04	0.04
Prior GED	0.04	0.04	0.04	0.04	0.04	0.04	0.04
Prior BA+	0.05	0.00	0.00	0.00	0.00	0.00	0.00
Prior AA	0.03	0.00	0.00	0.00	0.00	0.00	0.00
Prior CA HS Proficiency	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Educational Goals							
Transfer	0.62	0.92	0.92	0.92	0.92	0.92	0.92
AA (Not Transfer)	0.09	0.13	0.13	0.12	0.13	0.12	0.12
Vocational	0.11	0.05	0.05	0.05	0.04	0.04	0.04
Interest	0.06	0.03	0.03	0.02	0.02	0.02	0.02
Basic Skills	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Credit at Other Levels	0.10	0.05	0.05	0.05	0.04	0.04	0.04
N (Student Enrollments)	57,044,044	35,435,970	34,266,978	30,050,111	28,780,519	24,044,398	9,969,993

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. Educational goals not mutually exclusive and represent whether goal was ever named

Table 3 Demographic characteristics and modalities over time

	2015 (1)	2018 (2)	2021 (3)
Student Characteristics			
Hispanic	0.48	0.51	0.51
White	0.25	0.22	0.22
Asian	0.10	0.10	0.09
Black	0.07	0.06	0.06
Other Race	0.10	0.11	0.12
Female	0.53	0.54	0.55
Need-Based Aid	0.67	0.64	0.63
Age 25+	0.22	0.22	0.25
Modality			
FtF Course	0.84	0.78	0.26
Asynch	0.15	0.21	0.66
Synch	0.01	0.01	0.08
N (Student Enrollments)	3,496,379	3,628,719	2,844,895

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. FtF = face-to-face; Asynch = asynchronous; Synch = synchronous. Coll = College, Crs = Course, Stud = Student

Table 4 Descriptive statistics of sample (sample means)

	FtF (1)	Asynch (2)	Synch (3)
Hispanic	0.52	0.47	0.47
White	0.22	0.24	0.23
Asian	0.10	0.10	0.11
Black	0.06	0.07	0.07
Other Race	0.10	0.12	0.11
Female	0.51	0.59	0.54
Need-Based Aid	0.65	0.65	0.61
Age 25+	0.20	0.29	0.27
N (Student Enrollments)	6,525,117	3,190,985	253,891

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. FtF = face-to-face; Asynch = asynchronous; Synch = synchronous

Table 5 Characteristics of college-courses observed in single vs. multiple modes, student-term

	2015		2021	
	Mult. Modes	Single Mode	Mult. Modes	Single Mode
	(1)	(2)	(3)	(4)
Course Characteristics				
Basic Skills Course	0.03	0.02	0.02	0.01
Transfers to UC or CSU	0.92	0.85	0.93	0.86
CTE	0.22	0.37	0.15	0.41
Year-prior Pass Rate for FtF Course	0.69	0.77	0.71	0.79
Course Subject				
Humanities	0.13	0.06	0.13	0.06
Social Sciences	0.22	0.06	0.16	0.08
Math	0.07	0.04	0.14	0.03
Psychology	0.06	0.02	0.05	0.02
Bus & Mgmt	0.13	0.06	0.06	0.07
Fine Arts	0.07	0.18	0.09	0.16
Education	0.03	0.11	0.06	0.10
Fam/Consumer Sci	0.07	0.06	0.05	0.06
Inf. Tech	0.06	0.03	0.03	0.04
Pub/Protect Services	0.04	0.05	0.03	0.05
Biological Sci	0.02	0.03	0.05	0.03
Foreign Language	0.02	0.03	0.03	0.03
Engin./Indust. Tech	0.01	0.09	0.02	0.09
Media & Comm	0.02	0.04	0.02	0.04
Ag/Natural Resources	0.00	0.02	0.01	0.02
Arch/Env Design	0.00	0.01	0.00	0.01
Health	0.02	0.06	0.02	0.07
Env Sci & Tech	0.00	0.00	0.00	0.00
Law	0.00	0.01	0.00	0.01
Library Science	0.00	0.00	0.00	0.00
Mil Studies	0.00	0.00	0.00	0.00
Commer. Services	0.00	0.01	0.00	0.01
Interdiscipl. Studies	0.00	0.00	0.00	0.00
N (Unique College-Course-Terms)	9,810	93,329	12,060	83,765

Authors' calculations from CCCCO Data. Each unit represents a unique college-course-term cell. Samples correspond to year-specific sub-samples of Table 2, Column 5 (i.e., before we drop courses only ever offered in a single instructional modality)

Table 6 Characteristics of students observed in single vs. multiple modes, student-term

	2015		2021	
	Mult. Modes	Single Mode	Mult. Modes	Single Mode
	(1)	(2)	(3)	(4)
Student Characteristics				
Female	0.57	0.51	0.53	0.56
Hispanic	0.43	0.50	0.50	0.53
White	0.27	0.23	0.22	0.21
Asian	0.12	0.09	0.10	0.08
Black	0.07	0.07	0.06	0.07
Other Race	0.11	0.10	0.12	0.11
Use Need-Based Aid	0.67	0.63	0.62	0.56
Age 25+	0.26	0.28	0.21	0.38
N (Unique Student-Terms)	316,976	1,072,886	391,898	647,711

Authors' calculations from CCCCO Data. Each unit represents a unique student-term cell. Samples correspond to year-specific sub-samples of Table 2, Column 5 (i.e., before we drop courses only ever offered in a single instructional modality)

Appendix B: Sorting and Robustness Tests

In this appendix, we show a series of tests for sorting patterns that may raise concerns about biases in our results, and robustness tests to probe whether our results are sensitive to different model assumptions.

Sorting Tests

Our sorting tests test for bias using college-course-term fixed effect and student-term fixed effects strategies in turn. In practice, because we include both college-course-term fixed effects and student-term fixed effects in our main equations, we should closely control for both student and course characteristics that may bias our results. However, the sorting tests provide a sense of how concerned we should be in the first place that our results may be biased.

Testing for Sorting on "Student Propensity to Pass" within College-Course-Term FE Models

Potential bias in our college-course-term fixed effects models may arise if, within the same class and college (e.g., Bio 101 at College of the Sequoias), students sorting into synchronous or asynchronous courses are differentially likely to pass their courses in general. To test this, we generate a "propensity to pass" indicator that draws on data from FtF courses in fall 2019. We use this sample to estimate equations relating indicators for whether students pass each course to a vector of student characteristics ($\overline{Stud_{it}}$) as predictors. This vector includes variables capturing whether the student used need-based aid, whether students ever had a primary exceptionality/disability recorded, units attempted first term, any basic skills first term, vector of indicators for pre-entry credentials, vector of indicators for academic goals ever reported, and controls for sex, race, and age at first enrollment term:

$$Pass_{ijcst} = \gamma\overline{Stud_{it}} + \varepsilon_{ijcst}$$

We use the estimates from this equation to generate predicted probabilities of course passing ($\widehat{Pass}_{ijcst}$) for students in all course modes and years. We then estimate results for this "pseudo-outcome" in an equation using school-course-term fixed effects:

$$\widehat{Pass}_{ijcst} = \beta Synch_{jcst} + \delta Asynch_{jcst} + \theta_{cst} + \varepsilon_{ijcst}$$

If students who are less likely to pass opt into synchronous or asynchronous courses (relative to FtF), those coefficients will be negative. However, our results (Appendix Table 7) suggest that, if anything, students sorting into both synchronous and asynchronous courses tend to be more likely to pass their courses than are students in face-to-face courses. The extent of sorting is less extreme in the terms we observe post-COVID, however, consistent with students' choices being more constrained in those terms.

Note that results (Appendix Table 7) are, if anything, more positive for asynchronous than synchronous courses, even in 2021–22. This implies that the relative advantages for synchronous courses compared to asynchronous courses observed in our main results (Table 1) may, if anything, slightly understate the benefits of this format to student performance relative to asynchronous courses.

Results (available on request) are very similar if we estimate the "propensity to pass" equations including a vector of course subject indicators in the first stage.

Testing for Sorting on "Course Difficulty" within Student-Term FE Models

A second set of sorting tests addresses potential bias using student-term fixed effects models. A potential concern for these models is that students' decisions to take courses in online modalities may depend on how difficult they anticipate those courses to be. For instance, if students think that it is more challenging to pass online ccourses, they may take easier courses online. This would have the effect of producing positive biases on coefficients indicating online modalities: online course-taking would look artificially more positive if easier courses were taken online.

We test for whether such processes bias our results with another set of pseudo-outcomes estimating the expected difficulty for each course. We estimate course difficulty taking the fall 2019 face-to-face pass rate for each course. We use the 2019 FtF pass rate as a "pseudo-outcome" in equations using student-term fixed effects. If students take harder courses synchronously/asynchronously (relative to FtF), those coefficients will be negative:

$$FtF2019PassRate_{cst} = \beta Synch_{jcst} + \delta Asynch_{jcst} + \theta_{it} + \varepsilon_{ijcst}$$

We find that pre-pandemic, the courses students took online had systematically higher pass rates than the ones they took face-to-face (Appendix Table 8); this was especially true for synchronous courses. The same pattern remained true for asynchronous courses post-pandemic: compared to the courses they took face-to-face, the courses students took asynchronously tended to have pass rates that were roughly 0.2 percentage points higher. However, the pass rates for their synchronous courses in the 2021–22 academic year were roughly 2.3 percentage points lower than the courses they took face-to-face. This suggests that the advantages we estimate in our student fixed effects models that show benefits to synchronous courses relative to asynchronous courses as of the 2021–22 academic year (Table 1) may, if anything, understate the benefits to performance in these courses.

Robustness Tests

We conduct a series of robustness tests to explore whether different model specifications would change the overall tenor of our results. Appendix Table 9, Panel A presents the main results from Table 1, Panel B for comparison. Panels B and C show that our results are qualitatively similar if, instead of simultaneously entering the college-course-term and student-term fixed effects, we rely on either set of fixed effects in the absence of the other. We include student controls (e.g. sex, race, age at first enrollment term, whether the student used need-based aid, whether students ever had a primary exceptionality/disability recorded, units attempted first term, any basic skills first term, vector of indicators for pre-entry credentials, vector of indicators for academic goals ever reported) in place of the student-term fixed effects in Panel B, and college fixed effects with course-level controls (e.g., course subject area, career-technical education status, basic-skills vs. transfer-level indicators, and the year-prior course passing rate) in place of the college-course-term fixed effects in Panel C.

The student and course control variables that we include in lieu of the prior student-term and college-course-term fixed effects have a generally modest degree of missingness (Appendix Table 10); for most variables, missingness occurs for 2% or fewer observations. A few notable exceptions are variables observed in students' first terms, which are missing for 6% of students whose first term (recorded by the CCCCO) occurred prior to 2006 (the earliest year data was provided to us). To preserve information from cases with missing covariates, we include missing variable indicators. In both cases, the results are similar in pattern to Panel A, though generally more modest in magnitude.

Panel D excludes the controls that we create to capture section-level characteristics. Results are very similar to those in Pattern A, suggesting that selective sorting into peer or class size characteristics across modalities is not driving our results.

Panel E uses a different approach to classifying course modalities. In our main specifications, course sections are classified to course modes in a hierarchical way, in which course sections that have multiple course sessions (e.g., a lecture and a lab) are assigned to the most-online form they take. That is, course sections are classified as face-to-face only if no session is online, synchronous if any session is synchronous and no session is asynchronous; and asynchronous if any session is asynchronous. In practice, relatively few course sections are mixed in modality (less than 3% in 2015 and 2018 and around 6% in 2021; see Appendix Table 11), but Panel E takes a different classification approach that excludes course sections that have any mixing of modalities. Results are substantively similar to Panel A.

As an alternate approach, Panel F separates out hybrid courses from those that are solely asynchronous or solely synchronous (solely face-to-face courses remain the omitted category). We see similar coefficients on the solely-asynchronous and solely-synchronous measures compared to the main estimates with less granular coding; moreover, we see negative coefficients for most of the hybrid course measures as well.

Panel G adds back into the sample the handful of colleges that had no reported asynchronous online course offerings pre-COVID to ensure that our results are not sensitive to our sampling choices. As noted in the main text, we exclude these colleges from our main analysis, because evidence suggests that online courses in colleges that categorized all online courses as synchronous did not resemble the Zoom-based courses that became prevalent during the pandemic and that are of primary interest in our analysis. For instance, CCCCO descriptions of synchronous courses pre-COVID do not appear to consider synchronous course-taking as offering such video-based interaction. Examples of synchronous interaction given in a 2018 CCCCO report on online courses included courses as meeting, for instance, over instant message rather than video (California Community Colleges Chancellor's Office, 2018). Moreover, qualitative evidence from distance education leaders in the California Community Colleges system suggests that synchronous classes using technology like Zoom was rarely used pre-pandemic (Hart et al., 2025a). Thus, our main analyses exclude colleges where all pre-COVID online courses were reported as synchronous.

Because there were so few synchronous courses pre-pandemic outside of those colleges that offered only synchronous courses, our pre-pandemic results for synchronous courses differ somewhat compared to the main estimates when these colleges are excluded; for instance, the estimated coefficient for synchronous courses in 2015 is −0.120 in our main sample (excluding colleges with 100% synchronous online offerings) vs. −0.093 when these colleges are included. However, we see very similar results for 2021–22, suggesting that the relative advantages for synchronous vs. asynchronous courses post-pandemic are not driven by this set of colleges.

Panels H-J relax sample restrictions introduced in our main analyses, including, respectively, decisions to exclude interdisciplinary courses (which includes courses like orientations and student success courses, Panel H); to drop students without high school degrees or with prior college degrees (Panel I); and to drop students who did not aim for either an associate degree or transfer (Panel J). In all cases, results are substantively similar to our main results.

Appendix Table 12 presents the main results in interaction form. That is, these analyses pool the three focal years in our regression analyses—2015, 2018, and 2021—and include mode-by-year interaction terms to determine whether the gaps in outcomes for asynchronous and synchronous courses (compared to face-to-face courses) were systematically larger in 2015 and 2021 compared to 2018. The main effects of the asynchronous and synchronous terms represent course outcome gaps by modality as of 2018, while the interaction terms represent how much smaller or larger those gaps were in the other years in the sample. At the bottom of the table, we include terms representing the "total effects" of each modality in 2015 and 2021, which represents the linear combinations of the main effects for each modality and their year-specific interaction terms. Results are very similar to the main estimates presented in Table 1, and show that the changes in gaps that we observe are statistically significant.

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Appendix Tables

See Tables 7, 8, 9, 10, 11, 12, and 13

Table 7 Sorting test: student "pass propensity" by mode, school-course-term fixed effects estimates

	(1)	(2)	(3)
	2015	2018	2021
Online Asynch	0.015***	0.012***	0.006***
	(0.000)	(0.000)	(0.000)
Online Synch	0.014***	0.007***	0.001***
	(0.001)	(0.001)	(0.000)
Control Mean: FtF	[0.683]	[0.679]	[0.677]
N	3,496,379	3,628,719	2,844,895

Source: Authors' calculations based on CCCCO data, 2018–19. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Outcome is predicted propensity of a student to pass courses, given only student controls as predictors. Propensities estimated based off of face-to-face courses taken in fall 2019. Standard errors clustered by student-term. No other controls included

Table 8 Sorting test: course difficulty (2019 FtF pass rate), student-term fixed effects estimates

	2015	2018	2021
	(1)	(2)	(3)
Online Asynch	0.003***	0.004***	0.002***
	(0.000)	(0.000)	(0.000)
Online Synch	0.019***	0.018***	−0.023***
	(0.002)	(0.002)	(0.001)
Control Mean: FtF	*[0.694]*	*[0.697]*	*[0.699]*
N	3,153,067	3,432,787	2,681,956

Source: Authors' calculations based on CCCCO data, 2018–19. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Outcome is mean 2019 FtF pass rate of course. Standard errors clustered by student-term. No other controls included

Table 9 Robustness checks: 2015, 2018, 2021

	2015	2018	2021
	(1)	(2)	(3)
Panel A. Main Results			
Online Asynch	−0.083***	−0.071***	−0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.120***	−0.087***	−0.031***
	(0.012)	(0.009)	(0.003)
N	3,496,379	3,628,719	2,844,895
Panel B. Use College-Course-Term FE (Excl. Student FE)			
Online Asynch	−0.081***	−0.058***	−0.030***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.130***	−0.071***	−0.023***
	(0.011)	(0.011)	(0.004)
N	3,496,379	3,628,719	2,844,895
Panel C. Use Student-Term FE (Excl. College-Course-Term FE)			
Online Asynch	−0.071***	−0.053***	−0.044***
	(0.001)	(0.001)	(0.001)
Online Synch	−0.106***	−0.062***	−0.027***
	(0.005)	(0.004)	(0.001)
N	3,496,379	3,628,719	2,844,895
Panel D. Excl. Section Controls			
Online Asynch	−0.083***	−0.071***	−0.054***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.118***	−0.091***	−0.028***
	(0.011)	(0.009)	(0.003)
N	3,496,379	3,628,719	2,844,895
Panel E. Exclude Hybrid Courses (Any Two Modes: FtF, Asynch, Synch)			
Online Asynch	−0.091***	−0.076***	−0.062***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.124***	−0.090***	−0.032***
	(0.012)	(0.010)	(0.004)
N	3,411,729	3,530,912	1,710,179
Panel F. Model Hybrid Separately			
Only Asynch	−0.091***	−0.077***	−0.062***
	(0.002)	(0.002)	(0.002)
Only Synch	−0.124***	−0.091***	−0.032***
	(0.012)	(0.010)	(0.003)
Ftf-Online Hybrid	−0.043***	−0.030***	−0.032***
	(0.005)	(0.004)	(0.004)
Hybrid, Asynch/Synch	0.000	0.003	−0.039***
	(.)	(0.057)	(0.006)
N	3,495,428	3,627,916	1,826,722
Panel G. Include Colleges with All-Synch Online Courses			
Online Asynch	−0.083***	−0.070***	−0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.093***	−0.066***	−0.032***
	(0.007)	(0.005)	(0.003)
N	3,641,140	3,772,871	2,963,471
	2015	2018	2021

Table 9 (continued)

	2015	2018	2021
	(1)	(2)	(3)
Panel H. Include Interdisciplinary Courses			
Online Asynch	−0.084***	−0.072***	−0.059***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.119***	−0.089***	−0.031***
	(0.012)	(0.009)	(0.003)
N	3,612,015	3,750,150	2,933,271
Panel I. Include Students with All Prior Credential Profiles			
Online Asynch	−0.082***	−0.069***	−0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.117***	−0.086***	−0.031***
	(0.012)	(0.009)	(0.003)
N	3,767,017	3,953,805	3,133,414
Panel J. Include Students with All Ed. Goals			
Online Asynch	−0.084***	−0.071***	−0.060***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.116***	−0.085***	−0.031***
	(0.010)	(0.009)	(0.003)
N	4,845,346	4,878,790	3,924,517

Source: Author's calculation from CCCCO data. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Coefficient (cluster robust standard error). Standard errors clustered at college-course level. Panel B excludes student-term fixed effects and incorporates student controls including race, sex, age at first term, financial aid use, exceptionality, basic skills enrollment in first year, units attempted in first term, vector of indicators for prior credentials, and a vector of indicator for academic goals. Panel C excludes college-course-term fixed effects and instead includes a college fixed effect with course controls including a vector of indicators for subject; basic skills status indicator; transfer status indicator; CTE status indicator; and prior-year pass rate in face-to-face sections for course. Section controls in all models include section class size, section-level leave-one-out averages of the share of students ever exceptional, intending AA or transfer, on financial aid. Missing dummy variables included for all control variables

Table 10 Degree of missingness of sample

	Fraction missing
Student Characteristics	
Race Indicator Variables Missing	0.00
Female Indicator	0.01
Age at First Term Variable	0.06
Financial Aid Indicator	0.00
Exceptionality Indicator	0.00
First-Term Basic Skills Course-Taking Indicator	0.06
First-Term Units Attempted Variable	0.06
Prior Credential Vector	0.02
Course Load Vector	0.00
Section Characteristics	
Class Size Variable	0.00
Share Peers Using Financial-Aid Variable	0.00
Share Peers with Exceptionalities	0.00
Share Peers with AA or Transfer Goal	0.00
N (Student-Course Enrollments)	9,969,993

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. Section variables are used in all regressions. Student characteristics used only in robustness tests that exclude student-term fixed effects

Table 11 Fraction of enrollments in courses offered in different modes, by year

	2015	2018	2021
	(1)	(2)	(3)
Only FtF (Lab And/Or Lecture)	0.856	0.797	0.273
Only Asynch	0.130	0.186	0.613
Only Synch	0.005	0.005	0.071
Hybrid FtF-Online (Any version)	0.024	0.027	0.049
Hybrid, Asynch/Synch	0.000	0.000	0.015
N (Student Enrollments)	3,495,428	3,627,916	2,812,563

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. Mode refers to offering of the course section each student is enrolled in. Hybrid sections are those that use more than one instructional modes across different course sessions

Table 12 Results in interaction form

	(1)
Online Asynch: 2018	−0.070***
	(0.002)
Online Synch: 2018	−0.088***
	(0.009)
AsynchX2015	−0.013***
	(0.002)
SynchX2015	−0.033**
	(0.013)
AsynchX2021	0.014***
	(0.002)
SynchX2021	0.059***
	(0.010)
Total Effects	
Online Asynch: 2015	−0.083
	(0.002)
	[0.000]
Online Synch: 2015	−0.121
	(0.012)
	[0.000]
Online Asynch: 2021	−0.055
	(0.002)
	[0.000]
Online Synch: 2021	−0.029
	(0.003)
	[0.000]
N	9,969,993

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. Mode refers to offering of the course section each student is enrolled in. All models include student-term fixed effects and college-course-term fixed effects, as well as section controls. Section on total effects includes coefficients, standard errors (in parentheses) and p-values (in brackets) of linear combinations of main effect for each mode and interaction of modeXyear

Table 13 Checks on experience: 2015, 2018, 2021

	(1)	(2)	(3)
	2015	2018	2021
Panel A. Main			
Online Asynch	−0.083***	−0.071***	−0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.120***	−0.087***	−0.031***
	(0.012)	(0.009)	(0.003)
N	3,496,379	3,628,719	2,844,895
Panel B. Age 18–20			
Online Asynch	−0.086***	−0.071***	−0.062***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.121***	−0.081***	−0.038***
	(0.013)	(0.012)	(0.004)
N	1,709,059	1,832,797	1,428,122
Panel C. Age 21 +			
Online Asynch	−0.082***	−0.070***	−0.052***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.117***	−0.095***	−0.018***
	(0.013)	(0.010)	(0.004)
N	1,736,535	1,736,247	1,368,875
Panel D. First Term Students			
Online Asynch	−0.101***	−0.083***	−0.065***
	(0.005)	(0.004)	(0.004)
Online Synch	−0.126***	−0.089***	−0.037***
	(0.019)	(0.021)	(0.006)
N	437,172	478,434	409,078
Panel E. Returning Term Students			
Online Asynch	−0.083***	−0.070***	−0.056***
	(0.002)	(0.002)	(0.002)
Online Synch	−0.122***	−0.088***	−0.029***
	(0.012)	(0.009)	(0.003)
N	2,948,677	3,068,251	2,381,927

Authors' calculations from CCCCO Data. Each unit represents a student-course enrollment. Mode refers to offering of the course section each student is enrolled in. All models include student-term fixed effects and college-course-term fixed effects, as well as section controls

Appendix C Tabular Form of Subgroup Analyses

See Table 14

Table 14 Student subgroup pass/A/B/C differences by course modality, 2021–22

	(1)	(2)
	b	(se)
Panel A. Female Students		
Online Asynch	−0.060***	(0.002)
Online Synch	−0.031***	(0.004)
Outcome Mean: FtF	*[0.669]*	
P-val. Diff: Asynch-Synch	0.00	
N	1,559,727	
Panel B. Male Students		
Online Asynch	−0.054***	(0.002)
Online Synch	−0.029***	(0.004)
Outcome Mean: FtF	*[0.681]*	
P-val. Diff: Asynch-Synch	0.00	
N	1,261,541	
Panel C. Hispanic Students		
Online Asynch	−0.065***	(0.002)
Online Synch	−0.032***	(0.004)
Outcome Mean: FtF	*[0.637]*	
P-val. Diff: Asynch-Synch	0.00	
N	1,447,812	
Panel D. White Students		
Online Asynch	−0.049***	(0.003)
Online Synch	−0.026***	(0.005)
Outcome Mean: FtF	*[0.748]*	
P-val. Diff: Asynch-Synch	0.00	
N	620,938	
Panel E. Black Students		
Online Asynch	−0.065***	(0.006)
Online Synch	−0.035***	(0.010)
Outcome Mean: FtF	*[0.594]*	
P-val. Diff: Asynch-Synch	0.00	
N	177,992	
Panel F. Asian/PI Students		
Online Asynch	−0.033***	(0.004)
Online Synch	−0.020***	(0.007)
Outcome Mean: FtF	*[0.766]*	
P-val. Diff: Asynch-Synch	0.03	
N	264,230	
Panel G. Students Age 25 +		
Online Asynch	−0.044***	(0.003)
Online Synch	−0.009*	(0.005)
Outcome Mean: FtF	*[0.683]*	
P-val. Diff: Asynch-Synch	0.00	
N	701,285	
Panel H. Students Age 24-		
Online Asynch	−0.059***	(0.002)
Online Synch	−0.034***	(0.003)
Outcome Mean: FtF	*[0.673]*	
P-val. Diff: Asynch-Synch	0.00	

Table 14 (continued)

	(1)	(2)
N	2,143,531	
Panel I. Students Using Need-Based Aid		
Online Asynch	−0.056***	(0.002)
Online Synch	−0.029***	(0.003)
Outcome Mean: FtF	*[0.677]*	
P-val. Diff: Asynch-Synch	0.00	
N	1,787,679	
Panel J. Students Not Using Aid		
Online Asynch	−0.060***	(0.002)
Online Synch	−0.030***	(0.004)
Outcome Mean: FtF	*[0.672]*	
P-val. Diff: Asynch-Synch	0.00	
N	1,057,216	

Source: Author's calculation from CCCCO data. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Coefficient (cluster robust standard error). Standard errors clustered at college-course level. All models include college-course-term fixed effects and student fixed effects. All models include section controls: section class size and section-level leave-one-out averages of the share of students with the following: ever exceptional, intending AA or transfer, on financial aid. Missing dummy variables included for all control variables. Results correspond with Figure A5

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Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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