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

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Abstract

The COVID-19 pandemic ushered in both increased use of online courses in general, and the use of newer forms of online instruction like synchronous instruction. This creates 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, overall and across different 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. 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.

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The use of online courses in postsecondary institutions was growing rapidly prior to the emergence of COVID-19 (Ortagus, 2017) and increased further during the pandemic (Felson & Adamczyk, 2021). In addition to pushing more courses online, the pandemic also triggered significant alterations in the characteristics and formats of online courses available. One notable change was the widespread adoption of synchronous courses, allowing real-time interaction between students and instructors using platforms like Zoom. While synchronous instruction was rarely used pre-pandemic, it opened the possibility to significantly change the post-pandemic online education landscape (Hart et al., 2022). Yet, little 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 pivotal 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 state community college system in the country, boasting 116 colleges—to address important new 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.

In the field of learning sciences, scholars have identified several unique challenges associated with asynchronous online instruction. For instance, the greater degree of student control over the pace of their learning in online instruction may pose difficulties, particularly for those with limited experience with self-directed learning (Rovai, 2003; Guglielmino & Guglielmino, 2003; Bambara et al., 2009; Schulz & Ketcham, 2014; Bork & Rucks-Ahidiana, 2013; Nash, 2005; Doherty, 2006). 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 (Richardson et al., 2015; Garrison et al., 2003). Both features may contribute to poorer course outcomes for asynchronous online students compared to peers taking courses face-to-face (Xu & Xu, 2019). 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, synchronous instruction often 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., 2021; Hart et al., 2022). These requirements can pose potential obstacles for students who lack access to these resources, underscoring issues related to the digital divide and equitable engagement in synchronous learning. 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. We explore this question using both a broad population of students and for specific student subgroups (e.g., by sex, race/ethnicity, and financial aid use).

In addition, while a growing volume of prior studies have examined the effectiveness of online instruction – primarily asynchronous in nature – at open-access institutions like community colleges in terms of outcomes like course passing and course completion (e.g., Xu & Jaggars, 2011, 2013; Johnson & Mejia, 2014; Bettinger, Fox, Loeb, & Taylor, 2017; Hart, Friedmann & Hill, 2018), these studies were conducted prior to pandemic and many of them drew on data from a decade ago or more. The existing body of work generally indicates that student course outcomes—like course passing—tend to be lower in online courses compared to in face-to-face modalities (see Xu & Xu, 2019 and Sublett, 2019).[1]

However, with the increasing prevalence of online instruction and significant transformations in online education during the pandemic (Hart et al., 2022), 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. Even before the pandemic, some states had invested in improving learning management systems, pedagogy in online courses, and services like virtual advising and tutoring for online students (see the California Virtual Campus-Online Education Initiative in the CCC system; California Virtual Campus, n.d.). With the further escalation of investments in online education during the pandemic, it becomes increasingly pertinent to use recent data to provide up-to-date analysis of the effectiveness of asynchronous online instruction and synchronous online instruction relative to face-to-face delivery.

We find that enrollment in online courses showed steady growth before the pandemic, but experienced a substantial surge during the pandemic, accounting for approximately two-thirds of enrollments in the CCC system in 2020-21 and 2021-22. The expansion of synchronous instruction was especially notable relative to the low levels of this modality pre-pandemic. We found 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.

Methods

Data

We draw on student-course level data from the California Community Colleges Chancellor's Office (CCCCO) 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 most 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.

Our analytical sample excludes several groups: students without prior high-school credentials and those with prior post-secondary degrees; students who report academic goals other than transfer or receiving an associate degree; and students who are missing valid student identifiers. We also exclude student-by-course level data on enrollments in non-credit courses[2] and in "interdisciplinary" courses (e.g., tutoring sections, counseling sections, college success courses, etc.), 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).

A handful of colleges reported exclusively using synchronous instruction in online courses pre-COVID. Yet, as detailed in Appendix B, details from both state reports and from interviews with distance education leaders suggest that these courses likely do not feature video-based 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. This yields a sample of roughly 29 million enrollment records. We use this sample for our descriptive analyses of course enrollment patterns over time.

Given that the goal of our study is to compare student performance between course delivery format, our main, regression-based analyses 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. The main regression-based analyses in our paper draw on data from nearly 10 million student-course enrollments during the 2015, 2018, and 2021 academic years. Appendix Table A1 traces how our student sample changes as subsequent sample restrictions are added.

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. While our regression analyses focus only on courses that are offered in multiple modalities, 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. That is, we look at whether, for instance, 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 fixed-effect regression models. 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 A2) show that students age 25 and over—who are 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 (such as family obligations) would be accounted for by these additional fixed effect controls. 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.

Specifically, 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}):

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

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 our saturated models are designed to account for many potential sources of bias in our estimates, we have also conducted direct tests to assess student sorting (see Appendix B, Tables B1-B2). 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) and find that students who enroll in online sections (within college-course-term fixed effect models) tend to have, if anything, a higher likelihood of passing compared to their peers who opt for face-to-face sections. Similarly, we estimate course difficulty by estimating 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, students take courses with higher pass rates asynchronously post-pandemic, relative to face-to-face and synchronous courses.

This suggests that any decrements in performance in asynchronous courses in post-pandemic terms relative to other formats is unlikely to be due to 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.

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.

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 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, Table B3), 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 including the number of students in the section and section-level measures capturing the share of peers ever in basic skills (remedial) courses; ever recorded with an exceptionality; intending to earn an associates degree or transfer (vs. reporting non-degree or transfer academic goals); and 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.

We also use sex, race, 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;” and for students using need-based aid vs. not using need-based aid.

To account for missing data, we incorporate dummy variables for all control variables to preserve information from observations with some missing data.

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 (Figure 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 (Figure 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 pre-pandemic to roughly 7% of total enrollments in 2021-22.[3] The use of different online course types is not evenly distributed across colleges (Figure 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; see Appendix Figure A1). For other subjects, like education, the use of synchronous enrollments is quite limited (2% of enrollments synchronous).

Figure 3 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 overrepresented 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. With respect to financial aid use, students receiving need-based aid are somewhat more heavily represented among online asynchronous course-takers 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 a 7.8 percentage point gap in course passing rates in 2015 (Column 1) to a 6.8 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 11.3 percentage points in 2015 to 8.3 percentage points in 2018 to 3.1 percentage points in 2021.

The implications for student success in online courses post-pandemic should 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 passage rates in face-to-face 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). For instance, because some recent work has suggested that twoway 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. The stability of our results across specifications gives us added confidence that our estimates are accurate.

We also look at subgroup analyses of performance gaps during 2021 specifically (the most recent year of data; Figure 4). Results represent separate regressions for each student subgroup listed. The pattern of larger asynchronous/FtF than synchronous/FtF gaps is remarkably consistent across all groups, but is especially notable for certain groups. The most pronounced differences are 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, 2019), our study suggests that the student performance gap between asynchronous and face-to-face 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 four 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.

This change in online student performance could be the result of several factors. Community colleges across the state made substantial investments in support for online learning during the pandemic (Hart et al., 2022). 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., 2022), which may have resulted in improved quality of delivery of synchronous courses during the pandemic.

The pattern of performance gaps across modes may also 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 Hispanic students also have particularly large performance gaps between online and face-to-face classes. Moreover, 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.

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.

Endnotes

(1) A distinct but related question is how online course-taking affects longer-term outcomes like transfer and degree attainment; see Xu & Xu, 2019 and Sublett, 2019 for reviews on these questions.

(2) Non-credit courses include those not intended to contribute to a degree for course-takers in general, 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, n.d.). These constitute less than 15% of the total observations over the time period in question.

(3) If we include colleges where all pre-pandemic online courses were synchronous, the comparable figures are less than 1.5% of enrollments pre-pandemic being synchronous vs. 9% in 2021-22.

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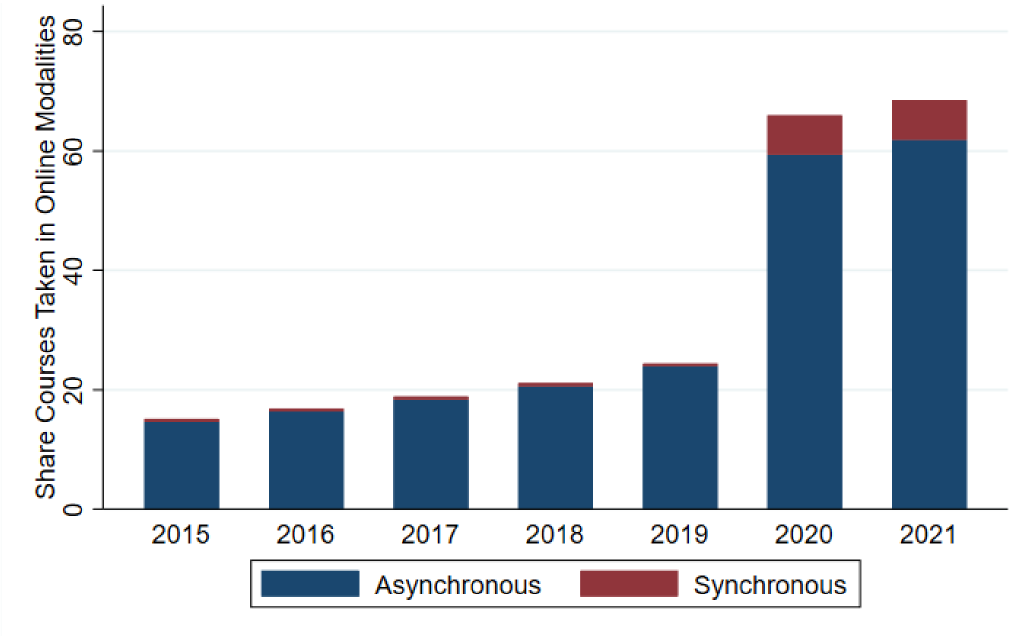
Figure 1

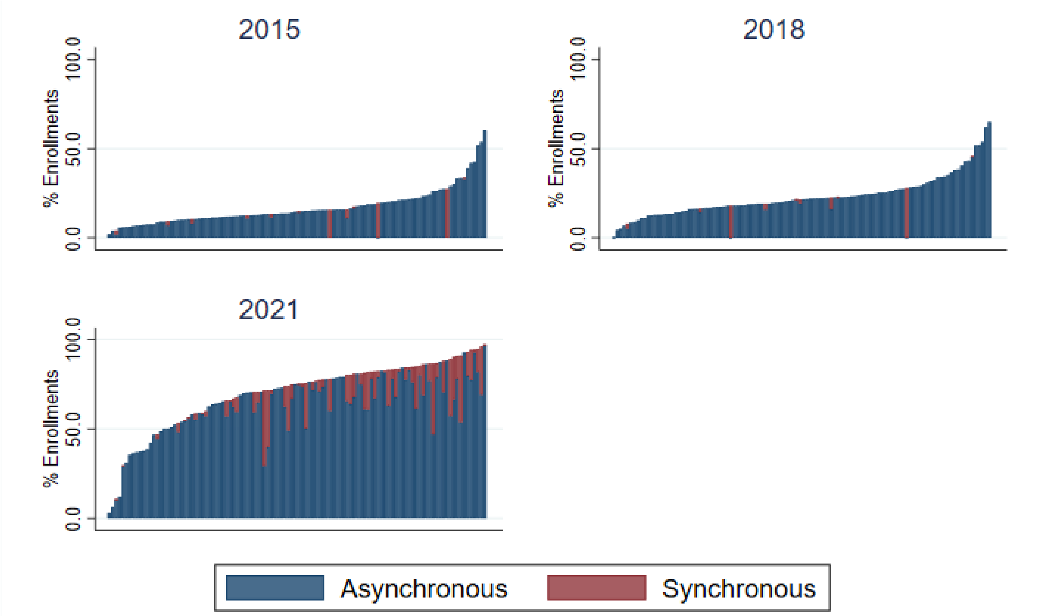
Share of Courses Taken in Online Modalities, Fall and Spring Terms by Year



Note: Authors' calculations from California Community Chancellor's Office Data. Years refer to year during fall term.

Figure 2

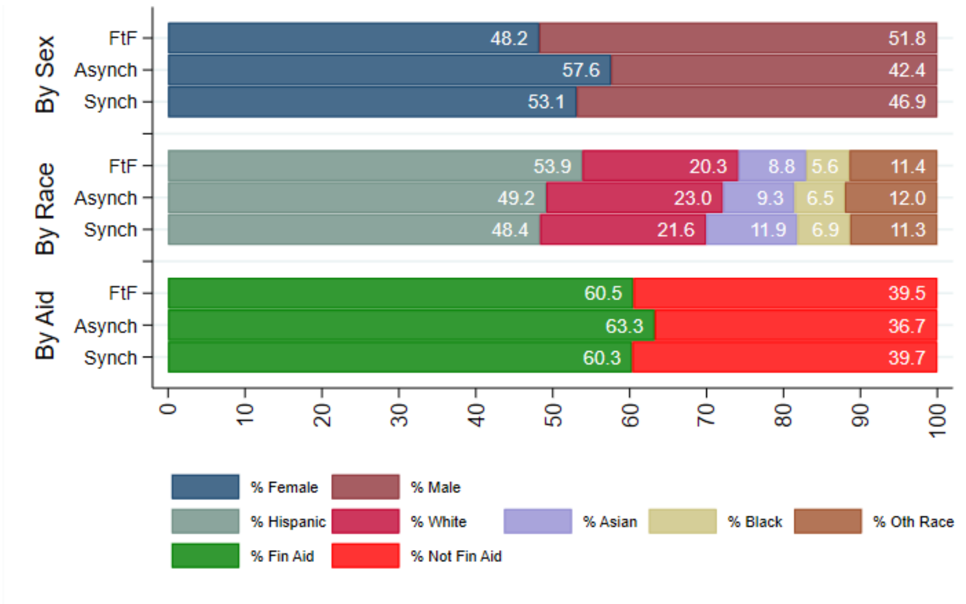
Distribution of Synchronous and Asynchronous Enrollments by College by Year



Source: Authors' calculations from CCCCO data, Fall 2018-Fall 2021. Each bar represents one college.

Figure 3

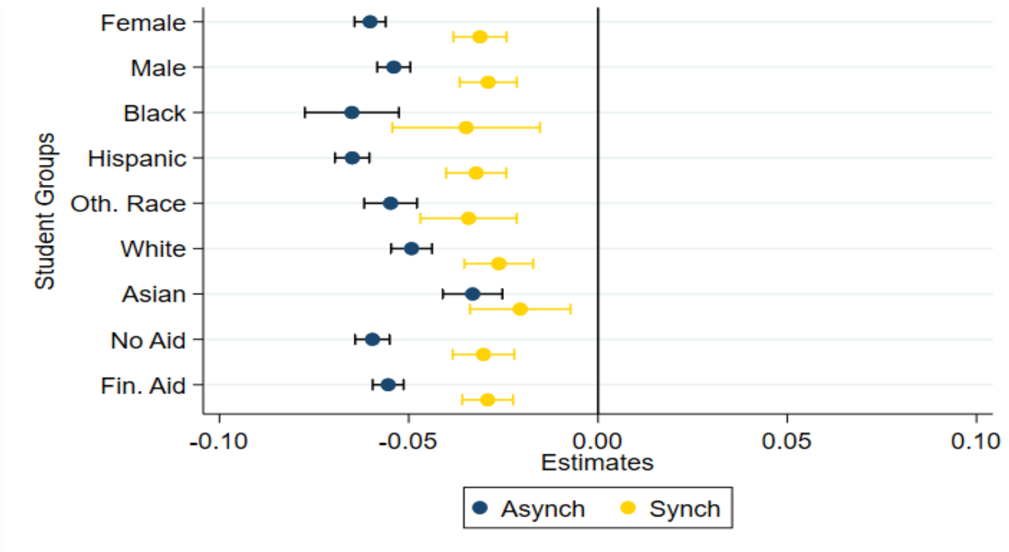
Race and Sex Characteristics by Mode, Fall 2021/Spring 2022



Note: Authors' calculations from California Community Chancellor's Office Data.

Figure 4

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.

Table 1

Main Results: Pass/A/B/C Rates by Modality, Relative to Face-to-Face Courses

	2015	2018	2021
	b/se	b/se	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	-0.078***	-0.068***	-0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	-0.113***	-0.083***	-0.031***
	(0.011)	(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	0.09	0.00

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Coefficient (cluster robust standard error). Standard errors clustered at college-course level. Panel A represents uncontrolled relationships between modalities and course passing. 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 in basic skills courses, 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.

Appendix A. Additional Tables and Figures

Appendix Table A1

Changes in Mean Student Characteristics as Sample Exclusions are Added

		Add Sample Exclusions Based On:					
	Full Sample	Prior Credential/ Ed. Goals	Interdisc.	Fall/ Spring	All-Synch	Mode Variation	2015, 2018, 2021
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
Has Dependents	0.21	0.20	0.20	0.19	0.20	0.19	0.20
Age 25+	0.31	0.24	0.24	0.24	0.24	0.23	0.23
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 (Stud. 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.

Appendix Table A2

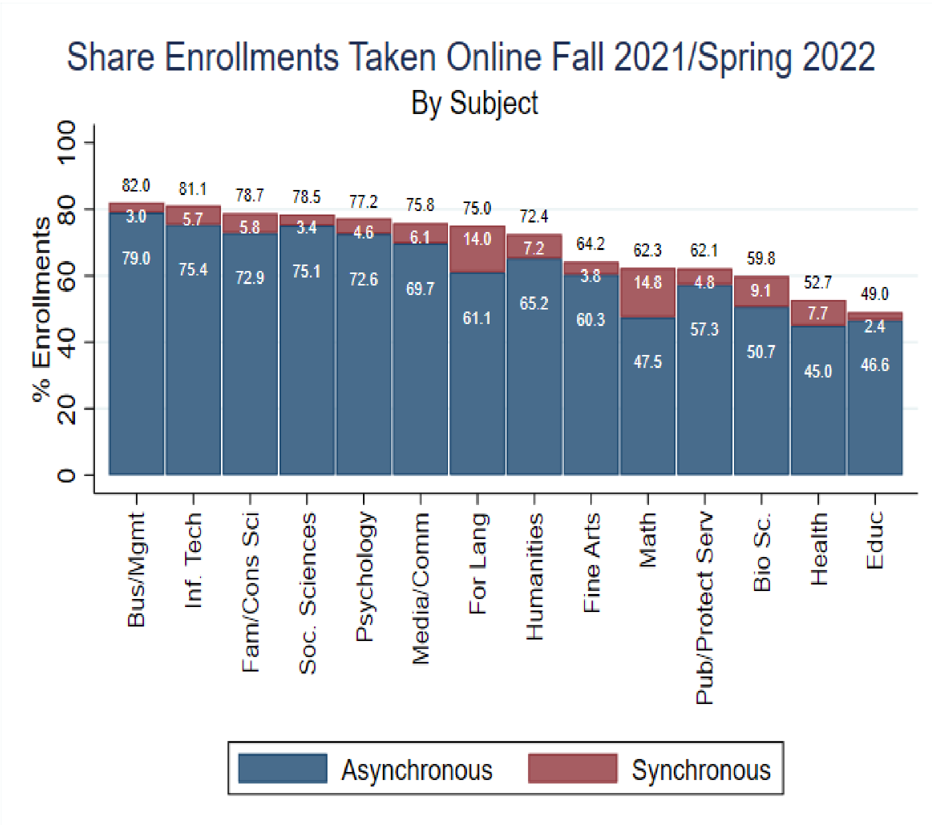
Descriptive Statistics of Sample (Sample Means)

	FtF	Asynch	Synch
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
Has Dependents	0.19	0.21	0.15
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

Appendix Figure A1

Share of Courses Taken in Online Modalities, 2021-22, by Course Subject



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 as predictors (e.g, whether the student used need-based aid, whether students ever had a primary exceptionality/disability recorded, whether the student reported having dependents, 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):

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

We use the estimates from this equation to generate predicted probabilities ($\widehat{Pass}_{ijcst}$) of course passing generated using coefficients from this equation, 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 B1) 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 B1) 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 courses, 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 equation using student 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 B2); this was especially true for synchronous courses. The same pattern remained true for asynchronous courses post-pandemic: compared to the courses they took online, 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. 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 B3, 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, whether the student reported having dependents, 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. In both cases, the results are similar in pattern to Panel A, though generally more modest in magnitude.

Panel D uses a different approach to classifying course modalities. In our main specifications, courses are classified to course modes in a hierarchical way, in which courses that have multiple course sessions (e.g., a lecture and a lab) are assigned to the most-online form they take. That is, courses 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 courses are mixed in modality (less than 3% in 2015 and 2018 and around 6% in 2021; see Appendix Table B4), but Panel D takes a different classification approach that excludes courses that have any mixing of modalities. Results are substantively similar to Panel A.

As an alternate approach, Panel E 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.

Finally, Panel F 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., 2022). 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 is -0.113 in our main sample (excluding colleges with 100% synchronous online offerings) vs. -0.087 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.

Appendix References

California Community Colleges Chancellor's Office (2018.) Distance Education Report: 2017 Report. https://www.cccco.edu/-/media/CCCCO-Website/docs/report/2017-DE-Report-Final-ADA.pdf

Hart, C.M.D., Hill, M., Alonso, E., & Xu, D. (2022). I don't think the system will ever be the same: distance education leaders' predictions and recommendations for the use of online learning in community colleges post-COVID. Annenberg EdWorkingPapers Series. https://www.edworkingpapers.com/ai22-687

Appendix Table B1

Sorting Test: Student "Pass Propensity" by Mode, School-Course-Term Fixed Effects Estimates

	(1) 2015	(2) 2018	(3) 2021
Online Asynch	0.014***	0.010***	0.004***
	(0.000)	(0.000)	(0.000)
Online Synch	0.012***	0.004***	0.001**
	(0.001)	(0.001)	(0.000)
Control Mean: FtF	*[0.684]*	*[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.

Appendix Table B2

Sorting Test: Course Difficulty (2019 FtF Pass Rate), Student-Term Fixed Effects Estimates

	(1) 2015	(2) 2018	(3) 2021
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 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.

Appendix Table B3
Robustness Checks: 2015, 2018, 2021

	(1) 2015	(2) 2018	(3) 2021
Panel A. Main Results			
Online Asynch	-0.078***	-0.068***	-0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	-0.113***	-0.083***	-0.031***
	(0.011)	(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	-0.072***	-0.052***	-0.028***
	(0.002)	(0.002)	(0.002)
Online Synch	-0.116***	-0.061***	-0.022***
	(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	-0.067***	-0.050***	-0.044***
	(0.001)	(0.001)	(0.001)
Online Synch	-0.099***	-0.059***	-0.027***
	(0.005)	(0.004)	(0.001)
N	3,496,379	3,628,719	2,844,895
Panel D. Exclude Hybrid Courses (Any Two Modes: FtF, Asynch, Synch)			
Online Asynch	-0.086***	-0.073***	-0.062***
	(0.002)	(0.002)	(0.002)
Online Synch	-0.117***	-0.086***	-0.032***
	(0.012)	(0.010)	(0.004)
N	3,411,729	3,530,912	1,710,179
Panel E. Model Hybrid Separately			
Only Asynch	-0.086***	-0.074***	-0.062***
	(0.002)	(0.002)	(0.002)
Only Synch	-0.117***	-0.086***	-0.032***
	(0.012)	(0.010)	(0.003)
Ftf-Online Hybrid	-0.042***	-0.028***	-0.032***
	(0.005)	(0.004)	(0.004)
Hybrid, Asynch/Synch	-	0.003	-0.039***
		(0.056)	(0.006)
N	3,495,428	3,627,916	1,826,722
Panel F. Include Colleges with All-Synch Online Courses			
Online Asynch	-0.078***	-0.067***	-0.058***
	(0.002)	(0.002)	(0.002)
Online Synch	-0.087***	-0.062***	-0.032***
	(0.007)	(0.005)	(0.003)
N	3,641,140	3,772,871	2,963,471

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 (race, sex, age at first term, financial aid use, parent status, exceptionality, basic skills enrollment in first year, units attempted in first term, prior credentials, and academic goals). Panel C excludes college-course-term fixed effects and instead includes a college fixed effect with course controls (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 in basic skills courses, ever exceptional, intending AA or transfer, on financial aid. Missing variable indicators included for all control variables.

Appendix Table B4

Fraction of Enrollments in Courses Sections Offered in Different Modes, by Year

	2015 mean	2018 mean	2021 mean
Only FtF (Lab And/Or Lecture)	0.856	0.797	0.262
Only Asynch	0.130	0.186	0.618
Only Synch	0.005	0.005	0.086
Hybrid FtF-Online (Any version)	0.024	0.027	0.047
Hybrid, Asynch/Synch	0.000	0.000	0.017
N (Student Enrollments)	3,495,428	3,627,916	1,826,722

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.