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# Going the Distance or Growing More Remote? The Academic Impacts of Course Modality following Pandemic-Era Investments

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**Going the Distance or Growing More Remote? The Academic Impacts of Course Modality following Pandemic-Era Investments**

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Abstract:
Since the COVID-19 pandemic, distance education has rapidly expanded, transforming the landscape of community colleges. This paper explores how different online learning modalities impact student success in the Los Angeles Community College District (LACCD), one of the largest and most diverse systems in the United States. With the purpose of providing actionable insights to community college leaders seeking to improve student outcomes and plan modality offerings moving forward, our analyses examine how student academic performance is influenced by participation in online courses and the extent of online course enrollment, as well as how outcomes vary based on course type, subject area, prior academic performance, and student demographics. Our findings suggest that enrolling in online courses leads to a slight reduction in students' GPAs, has no impact on credits earned, and has a moderate negative effect on persistence. Negative impacts are driven by dosage of online course taking, modality choice, and course subject.

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The COVID-19 pandemic fundamentally transformed the landscape of postsecondary education, with significant declines in community college enrollment of 8.9 percent in Fall 2020 and 6.8 percent in Fall 2021 and only modest recoveries of 0.4 and 2.7 percent increases the next two years (National Student Clearinghouse, 2024). Community colleges responded to both campus closures and enrollment declines by expanding distance education offerings (also referred to as online or remote learning) to maintain student engagement and enhance accessibility. Some community college administrators viewed the transition to primarily online education as a temporary adaptation (Kurlaender et al., 2024; Orchard, 2023), but both student and faculty demand for remote instruction persisted beyond the end of the pandemic. In fact, the share of community college students taking online courses increased from 34 percent in 2019 to 58 percent in Fall 2022 (National Center for Education Statistics [NCES], 2022).

These changes highlight an ongoing tension in the structure of community college courses. Community colleges offer an affordable pathway to higher education and economic mobility for low-income, first-generation, and students of color (Chetty et al., 2017; Connolly, 2021); however, these institutions often have low average completion rates.[1] Community colleges face a significant dilemma: while many administrators believe that students prefer online education over the traditional in-person course format (Jaschik & Lederman, 2021), research demonstrates that students generally achieve poorer outcomes in virtual settings compared to in-person classrooms (Alpert et al., 2016; Bettinger et al., 2017; Kofoed et al., 2021; Xu & Jaggars, 2013, 2014). Compounding this issue is the concern that as distance learning expands, it increasingly attracts students who may be ill-suited for this educational format. If so, the performance gap between online and in-person

[1] Six-year national completion rates from 2017 are 43 percent for two-year community colleges and 67 percent for public four-year colleges (National Student Clearinghouse, 2023). The differences in the completion rates have been extensively studied and reflect intersecting barriers to degree completion such as work and caregiving responsibilities, inadequate transportation infrastructure, food insecurity, and risks of disruptive financial shocks. (Crespi et al., 2021; Maroto et al., 2015; Porter & Umbach, 2019).

instruction could widen as virtual course offerings become more prevalent and reach a broader student population less equipped to succeed in self-directed learning environments. Perhaps not surprisingly, community college students and faculty are also divided about the importance of—and tradeoffs to—distance education (Swanson et al., 2023; Thai et al., 2023).

We focus in this paper on the expansion of distance education in the Los Angeles Community College District (LACCD), the largest community college district in California and one of the largest and most diverse systems in the country. LACCD is in many ways a microcosm of the national community college landscape, having rapidly expanded distance education offerings, investing heavily in faculty development and student technological access to distance education modalities, and, at the same time, expressing concerns about the efficacy of these modalities. LACCD's large and diverse student body is also representative of the national demographic profile of community college students (Community College Research Center, 2021).

LACCD responded rapidly to the challenges of the pandemic by expanding its online learning infrastructure and support. Before the pandemic, about one-third of students were taking online courses, but by Fall 2020, all students were engaged in online learning, and even after the pandemic, in Fall 2022, around 60 percent of course sections in LACCD were in an online modality. To facilitate this shift, LACCD distributed roughly 40,000 devices to students, provided internet access resources, and allocated nearly $160 million in student aid. The district also invested heavily in technology for faculty and staff, enhancing internet infrastructure and purchasing cloud-based software platforms. Further, LACCD has offered nearly 400,000 hours of faculty training, allocated over $700,000 in professional development stipends, and provided funding for Distance Education Coordinators and trainers[2]. Despite these investments, LACCD leadership has expressed reservations about continuing to offer large shares of courses online. Francisco Rodriguez,

[2] Estimates from LACCD internal records.

LACCD's chancellor from 2014 to 2024, remarked, "We're returning to that more normal, in-person environment, but we're not quite there yet. We're about 50% online or hybrid and 50% in-person and working our way toward an environment that will be more in-person" (Orchard, 2023).

In this context, there is a need for research on the effects of distance education on student academic outcomes that reflects changes made in the wake of the pandemic. Researchers and policymakers alike need a clearer understanding of whether the impacts of distance education have changed given the investments in improving online course quality, any potential differences in effects across modalities within the broad distance education category (e.g., synchronous, asynchronous, hybrid, and HyFlex), and any variation in effects by course or student characteristics. With this in mind, we address the following research questions in the context of LACCD.

1. What is the impact of attempting credits in distance education modalities on student academic outcomes?
    a. How do these effects vary by the share of credits attempted in distance education modalities?
    b. How do these effects vary by the type of distance education modality attempted?
    c. How do these effects vary across student populations?
2. What is the impact of switching the modality of a course on student academic outcomes?
    a. How do these effects vary by course subject?
3. What is the relationship between student academic performance in an online course and future modality selection and academic performance in online courses?

## Prior Evidence on the Effects of Course Modality

We examine four distance education modalities in this paper. Asynchronous online courses allow students to complete all assignments and view recorded lectures on their own schedule. Synchronous online classes utilize platforms like Zoom to conduct live sessions, facilitating real-time engagement without a physical meeting space. Dual delivery/HyFlex classes offer students the choice between attending in-person or virtually on a session-by-session basis, often using technology such as Owls or built-in cameras and microphones to facilitate communication. Hybrid/blended learning classes combine in-person instruction with online sessions. Throughout the paper, we use the terms distance education, remote instruction, and online education interchangeably. In-person classes refer to face-to-face instruction in an assigned room on campus.

*Affordances and Challenges of Distance Education*

Distance education offers several advantages to students, including flexibility, accessibility, and the ability to cater to diverse learning needs (Hajibayova, 2017; Kurlaender et al., 2024). Synchronous, hybrid, and dual delivery/HyFlex courses allow students to benefit from flexible scheduling while still having opportunities for face-to-face interaction with classmates and professors (Kim & Sax, 2017; Kuh et al., 2008). At the same time, distance education has several well-documented drawbacks. Students likely need strong self-discipline and study skills, reliable access to technology, and the ability to be productive in the absence of direct classroom interactions with other students (Bork & Rucks-Ahidiana, 2013). Beyond academic skills, the lack of face-to-face interaction, particularly in asynchronous courses, can lead to feelings of isolation from both peers and instructors, potentially making it harder for students to engage and ask questions (Cole et al., 2021; Kofoed et al., 2021; Xu & Jaggars, 2014).

Interaction between students and professors may also suffer in courses delivered in online modalities, as it is common for students to keep their cameras off and refrain from engaging with their peers and professors (Swanson et al., 2023). Students may perceive less oversight from instructors in asynchronous and synchronous settings, in part because the challenge of identifying struggling students hinders the ability of instructors to provide specialized support and to adjust the course based on student progress (Bettinger et al., 2017; Swanson et al., 2023). Given the potential of distance education modalities to expand access to college and create barriers to success, there is an empirical question about the impacts of these modalities on student academic outcomes, which past work has attempted to answer.

*Student Performance in Online Education*

Pre-pandemic randomized trials consistently found that asynchronous and synchronous courses led to significantly lower grades and test scores for students relative to traditional in-person instruction (Alpert et al., 2016; Figlio et al., 2013; Joyce et al., 2015; but see Bowen et al., 2014). Past non-experimental studies at two- and four-year colleges have typically found negative and significant impacts of online education, particularly asynchronous learning, on course performance and persistence (Bettinger et al., 2017; Bettinger & Loeb, 2017; Xu & Jaggars, 2013, 2014). Researchers examining these questions in the context of California community colleges have also found negative impacts of distance education (Hart et al., 2018; Johnson & Cuellar Mejia, 2014).

Past research has found some differences in the efficacy of different online modalities. For instance, there may be advantages to taking asynchronous rather than synchronous courses (Palacios & Wood, 2016) and to taking hybrid rather than HyFlex courses (Calafiore & Giudici, 2021). In terms of overall course planning, there is some evidence in favor of a mix of online and in-person courses in each semester (Barrow et al., 2024; Ortagus, 2022; Shea & Bidjerano, 2018). Consistent with these past findings, early evidence about the effects of distance education post-pandemic finds a significant drop in course completion rates (Bird et al., 2022; Rodríguez-Planas, 2022) and a decline in first-year retention (Rodríguez-Planas, 2022). Similarly, a randomized trial conducted in Fall 2021 found that students assigned to an online version of an introductory economics course performed worse than those in the in-person version (Kofoed et al., 2021).

*Inequities*

A particularly concerning issue is that online education appears to exacerbate existing disparities in academic outcomes across different student populations. Notably, multiple studies have found that Black and Hispanic students, male students, and students with weaker academic preparation are more adversely affected by asynchronous, synchronous, and generally defined online courses compared to their peers from other groups (Bettinger et al., 2017; Figlio et al., 2013; Hart et al., 2018; Ortagus, 2022; Xu & Jaggars, 2014). These trends are especially concerning for community colleges, given that these populations are highly concentrated at these institutions (NCES, 2022).

Early evidence about the effects of distance education post-pandemic suggests possible increases in existing disparities and the development of new disparities. A comparison of midterm and final course grades indicated that students from neighborhoods with better broadband access benefited more from the shift to online learning (Altindag et al., 2021). Further, many students, particularly those from low-income backgrounds, reported having to delay their graduation after the Spring 2020 term (Aucejo et al., 2020; Rodríguez-Planas, 2022). The continued reliance on online course modalities and early evidence of concerning trends in student success post-2020 highlights the need to understand how course modality affects student outcomes. This understanding is essential to identify areas of success and concern, guiding efforts to enhance recovery and maximize student success moving forward.

## Data and Methods

### *Context and Data*

We use student-level administrative data from LACCD for all analyses. LACCD encompasses nine campuses and enrolls over 100,000 students annually. More than two-thirds of LACCD students attend part-time, and almost half of incoming students aim to transfer to a four-year institution. All nine LACCD campuses are Minority-Serving Institutions, each designated as a Hispanic-Serving Institution, with over 25 percent Hispanic enrollment. Additionally, Los Angeles

City College and Los Angeles Harbor College are recognized as an Asian American and Native American Pacific Islander-Serving Institution and Los Angeles Southwest is recognized as a Predominantly Black Institution (Minority Serving Institutions Exchange, 2024).

Our data spans the 2017-2018 to the 2023-2024 school years and includes student demographic information, transcript records, and financial aid information. Our sample comprises first-time in college (FTIC) students in their first semester at LACCD (N=86,911) and continuing students (N=244,036) who were enrolled in the nine LACCD colleges and took courses during fall and spring terms in the 2017-2018, 2018-2019 and 2021-2022 through the 2023-2024 school years. We exclude the 2019-20 and 2020-21 school years from the sample due to data issues that prevent us from accurately classifying the modality of courses. We also exclude career and technical education (CTE) courses in our main analyses, as these courses are more likely to be offered in person and have higher pass rates that could bias our assessment of the impact of online courses.

*Descriptive Statistics*

Table 1 presents descriptive statistics for our sample broken out by student type (FTIC vs continuing) and period (pre- vs post-pandemic). Consistent with community college populations nationwide, over half of the sample received need-based financial aid, either through a Pell Grant or a Board of Governor's (BoG) waiver (now called the California Promise grant). More than 60 percent of students in our sample identified as Hispanic, and nearly half were over 24 years old. On average, students enrolled in 7 to 9 credits during the fall semester, with overall credit loads slightly decreasing after COVID. First-time students attempted more credits than other students on average, both before and after the pandemic. Descriptive analyses not represented in Table 1 also show that students enrolled in at least one online credit generally attempt more credits in a term than their fully in-person peers, both before and after the pandemic. We also find that students who stopped out and returned to college were more likely to take all their credits online than those who did not leave.

Academic performance varied across time periods and student groups. Fall average GPAs ranged from 2.03 to 2.59, with continuing students usually earning higher GPAs than FTIC students. Post-pandemic, continuing students achieved higher GPAs, while FTIC students saw a decline in their GPAs. About 70 percent of students persisted from fall to spring, with post-COVID persistence rates slightly lower overall. Regardless of time period, FTIC students were more likely to persist than continuing students. On average, students completed courses and earned about the same percentage of attempted credits both before (69 percent) and post-pandemic (67 percent), with FTIC students securing a smaller share of their attempted credits.

*Methods*

We use a mix of descriptive and quasi-experimental approaches to answer our research questions. To address Research Question 1 about the effects of attempting credits in online modalities on student academic outcomes, we estimate effects using an inverse probability of treatment weighting approach. We use a course fixed effects model to address Research Question 2, about the impact of switching course modality and variation by subject. We use a descriptive linear regression to address Research Question 3, which is about the relationship between initial and future performance in online course modalities. Below, we describe each research question's outcomes, sample, and analytic approach.

*Research Question 1*

*Outcomes and Samples.* Research Questions 1, 1a, 1b, and 1c estimate the overall impact of online course taking on academic success. For these questions, we limit the sample to FTIC and continuing students enrolled in credit-bearing courses in the fall term and consider three primary outcome variables: fall semester credits attained; fall semester GPA; and persistence to the spring semester, measured as a binary variable indicating whether or not the student enrolls in the subsequent spring semester. For Research Questions 1a and 1b, we restrict the sample to students enrolled in the 2021-22 through 2023-2024 school years, as there was not enough variation in online course enrollment pre-pandemic to support the analysis in those years. For our analysis examining fall GPA outcomes, we include only students enrolled in courses that count toward GPA calculations (excluding those exclusively taking pass/fail courses). Additionally, when analyzing persistence, we remove any students who either completed their credentials during the fall term or who have credential completion records but no enrollment records for the spring term[3]. Our preferred specification only includes fall term outcomes because annual outcomes include selective attrition after fall term; however, supplemental analyses in the Appendix include both fall and spring semesters, with outcome variables including (1) cumulative credit accumulation across both semesters; (2) average GPA across the fall and spring semesters, and (3) a binary variable indicating whether the student re-enrolls in the subsequent fall semester.

*Analytic Approach for RQ 1:* We use an inverse propensity score weighting strategy to estimate the impact of taking any online credits in a term on students' academic outcomes. Table 2 presents descriptive statistics for the fall outcome samples, broken out by online course participation. This table shows differences in the composition of students who opt for online courses compared to those who do not. Given these differences, it is crucial that our modeling addresses selection into online coursework to better identify the impacts of attempting credits online on outcomes. To accomplish this, we use an inverse propensity score weighting approach to mimic random assignment to online courses. Specifically, we weight observations based on the inverse of the probability that student $i$ would receive the treatment (in this case, online education) given their

[3] This exclusion may introduce bias into our results, as it could disproportionately affect the sample of students who take distance education. If a larger proportion of distance education students complete their credentials quickly compared to those who do not, our treatment sample may overrepresent less academically inclined students. To assess potential bias, we include graduates in our analyses and conduct descriptive analyses to determine whether the time to credential differs based on online course enrollment. Our findings indicate that students who enroll in any online courses generally take longer to complete their credentials than those who attend solely in-person classes, and our estimates remain unchanged when these students are included. Consequently, we are confident that this sample specification does not impact our results.

baseline characteristics. We begin by estimating the following Equation (1) to generate a propensity score (*p*) for each student.

$$\hat{Y}_{it} = \alpha + \delta X_{it} + \boldsymbol{\tau}_j + \varepsilon_i \text{ (1)}$$

$\hat{Y}_{it}$is an indicator for whether student *i* took any online courses in a term. $X_{it}$is a vector of student characteristics, which includes factors that may affect selection into online courses. Namely, we include Pell and/or Board of Governor's waiver (BoG; CA Promise grant) eligibility to account for the financial aid status of students, as well as Los Angeles College Promise[4] (LACP) participation to control for students' involvement in an academic support program that might impact their choices and success[5]. We also include gender, race/ethnicity, and a categorical age indicator, as these factors are often associated with varying levels of access to resources and support (Glowacki-Dudka, 2019; MacDonald, 2018; Reeves & Smith, 2021)[6]. We also include enrollment intensity (part vs. full-time). $\tau_j$ a campus fixed effect, which controls for the availability of online courses at a campus, as well as other campus-level factors that may impact selection into online education. $\varepsilon_i$ is an error term clustered by student.

Due to differences in the distribution of credits attempted online between FTIC and continuing students and between the pre- and post-pandemic periods, we estimate propensities separately by group: FTIC and continuing students pre- and post-pandemic, respectively (see Table 1). We then combine the datasets containing student characteristics and propensity scores to

[4] LACP is a comprehensive support system that offers financial, academic, and personal support to first-time in college students enrolled full-time in LACCD.

[5] We do not control for Extended Opportunity Programs & Services (EOPS) status, as most students who partake in this program also receive Pell Grants and participate in the LA College Promise. EOPS is a retention and support program designed to improve student success for those who have experienced economic and educational hardships.

[6] Gender is defined as male, female, or non-binary. Race/ethnicity is broken into eight categories and includes Hispanic, White, Black, Asian, Filipino, Pacific Islander, American Indian, and Multiethnic. Age is broken into five categories and includes under 20, 20-24, 25-34, 35-54, and 55 and over.

estimate the effects of online course taking jointly. We generate inverse probability of treatment weights (*w*) for each student, as shown in Equation (2). For comparison units:

$$w = \frac{p}{1-p} \quad (2)$$

For treated units:

$$w = 1 \quad (2)$$

To ensure overlap between samples, we trim observations with propensity scores that do not overlap with the opposing group (treatment or control). Further, to reduce to influence of observations with very large or very small weights, we winsorize observations at the 1st and 99th percentiles (Thoemmes & Ong, 2016). Table 3 presents the results from joint significance tests before and after weighting and standardized mean differences between covariates before and after weighting, demonstrating that the weights help reduce bias between the treatment and comparison groups. We then apply these weights to our outcome model, as seen in Equation (3).

$$Y_i = \alpha + \gamma Online_{itj} + \varphi Covid_t + \beta Online_{itj} \cdot Covid_t + \delta X_{it} + \boldsymbol{\tau}_j + \boldsymbol{\lambda}_t + \varepsilon_i \quad (3)$$

$Y_i$ is, in turn, an indicator for whether student *i* is enrolled in LACCD for the next semester, fall-semester credit accumulation, and fall GPA. $Online_{itj}$ is an indicator variable, which indicates whether student *i* took courses online in term *t* at campus *j*. $Covid_t$ is an indicator for whether the term was prior to or after the onset of the COVID-19 pandemic. We include each indicator and the interaction term in the model and report marginal effects to show the effect of online course-taking pre- and post-pandemic. $X_{it}$is a vector of student characteristics. $\tau_j$ a campus fixed effect. $\lambda_t$ is a series of year fixed effects. $\varepsilon_i$ is an error term clustered by student. Additionally, we estimate a separate model where we replace $Covid_t$ with a categorical variable representing each year in the analysis (2017-2018 and 2018-2019 are grouped together), which allows us to estimate year-specific impacts of online education.

*Analytic Approach for RQ 1a:* To understand the relationship between the dosage of online course taking and students' outcomes, we estimate a propensity score model with weights as defined in Equations (1) and (2); however, rather than treatment as a binary indicator indicating whether students enrolled in any online coursework, we generate three binary treatment variables to indicate dosage of online coursework. To accomplish this, we divide students who took distance education courses in the 2021-22 through 2023-2024 school years into four groups: 1 to 29 percent, 30 to 59 percent, 60 to 99 percent, and 100 percent of credits attempted online. Students who attempted no credits online are always the reference group. This approach enables us to explore how different intensities of online education influence student outcomes, relative to taking all courses in person. As above, we generate propensity scores for FTIC and continuing students separately within each treatment group.

After we generate weights, we estimate the outcome model as seen in Equation (4):

$$Y_i = \alpha + \beta Online_{itj} + \delta X_{it} + \boldsymbol{\tau}_j + \boldsymbol{\lambda}_t + \varepsilon_i \quad (4)$$

$\beta Online_{itj}$ is our primary variable of interest and reflects the impact of the dosage of online course taking (1-29, 30-59, 60-99, and 100 percent, respectively). We estimate the outcome regression for each of the treatment indicators and compare point estimates from each model to understand how treatment effects vary by dosage. We again control for student characteristics, campus, and year in the model.

*Analytic Approach for RQ 1b:* To understand whether outcomes are driven by courses in a certain modality, we examine how outcomes vary based on credits taken in asynchronous and synchronous courses. Treatment is defined using three separate binary variables, which indicate whether a student took only asynchronous courses, only synchronous courses[7], or both modalities in

[7] LACCD codes hybrid (partially online and partially in-person) and HyFlex (allowing students to choose between online or in-person attendance) course formats as synchronous in the administrative data. As such, we are unable to separately estimate the impact of HyFlex, hybrid, and fully remote synchronous courses.

a term. Students who took no credits online are always the reference group. We estimate three propensity scores using the same covariates as in Equation (1), each time changing the treatment variable (only asynchronous, only synchronous, both). After we construct weights as given in Equation (2), we estimate the outcome model shown in Equation (5):

$$Y_i = \alpha + \beta Online_{itj} + \delta X_{it} + \boldsymbol{\tau}_j + \boldsymbol{\lambda}_t + \varepsilon_i \quad (5)$$

$\beta Online_{itj}$ is our primary variable of interest, with the $\beta$ coefficient capturing the impact of the modality of online course taking. We fit the outcome regression for each of the treatment indicators described above. We then compare point estimates from each model to understand how the treatment effect varies by modality of courses taken.

*Analytic Approach for RQ 1c:* Using OLS estimation, we conduct a series of descriptive subgroup analyses to explore how the relationship between online course enrollment and academic success varies across student populations. The main predictor is the number of online credits a student took each fall term. We start by investigating whether outcomes differ between FTIC and continuing students. Next, using interaction terms between online credits taken and the subgroup indicator of interest, we analyze how outcomes vary based on receipt of need-based aid (Pell or BoG grant) and age (younger than 24 vs. 24 or older). These models include controls for student characteristics, number of credits attempted, and campus and year fixed effects. For simplicity, we focus on post-COVID impacts and, for the models examining heterogeneity by age and need-based aid receipt, we limit our analysis to fall enrollment among FTIC students.[8]

*Sensitivity Checks.* For analyses corresponding to Research Questions 1-1b, we conduct a series of sensitivity checks to test the robustness of our findings: (1) excluding developmental

[8] Results are consistent across term and annual analyses.

education (remedial) courses[9]; (2) including CTE courses; (3) excluding students who took more than a full-time course load.

*Research Question 2.*

*Outcomes and Samples.* Research Questions 2 and 2a examine student outcomes at the individual course level, once again restricting the sample to FTIC and continuing students enrolled in the fall term. For Research Question 2, we consider the most heavily enrolled courses (Math 227, English 101, Political Science 001, Psychology 001, and Communications 101) during fall and spring terms in the 2017-18, 2018-19 and the 2021-22 through 2023-2024 school years. We expand the scope slightly to the 11 most popular courses at LACCD for Research Question 2a to group courses by subject area (humanities, STEM, and social sciences[10]) and ensure a large enough sample for analysis. Consistent with Hart et al. (2018), we consider three binary outcome measures at the course level: (1) completing the course, meaning not withdrawing from the course; (2) passing the course with a grade of A through C or "Pass" conditional on completion; (3) achieving a grade of A or B conditional on completion.

*Analytic Approach for RQ 2:* We replicate Hart et al. (2018), which estimates the impact of online course taking at the course-level, as shown in Equation (6).

$$Y_{ic} = \alpha + \gamma Online_{ic} + \varphi Covid_t + \beta Online_{ic} \cdot Covid_t + \delta X_{it} + \boldsymbol{\tau}_{cj} + \varepsilon_i \quad (6)$$

$Y_{ic}$ is, respectively, an indicator for each course-level outcome of interest. $Online_{ic}$ indicates that student *i* took course *c* in an online format. $Covid_t$ is an indicator for whether the term or academic

[9] A comparison of the results with and without developmental education classes in the sample is of interest because California passed legislation (AB 705) in 2017 (implementation required in 2019) that changed assignment practices and resulted in both fewer students being placed in developmental education coursework and a reduction in the number of developmental education courses offered at LACCD and other colleges in the state.
[10] Humanities courses (Communications 101, English 101, 102, and 103), STEM courses (Math 227, Anatomy 001, and Biology 003), and social sciences (Sociology 001, Psychology 001, Anthropology 101, and Political Science 001).

year was after the onset of the COVID-19 pandemic. $X_{it}$is a vector of student characteristics. $\tau_{cj}$ a campus-course fixed effect. $\varepsilon_i$ is an error term clustered by student[11].

*Analytic Approach for RQ 2a:* We replicate the model presented in Equation (6) but estimate models separately by subject. This allows us to compare estimated effects to determine if the impact of attempting credits online differs by subject.

*Sensitivity Checks.* For Research Questions 2 and 2a, we perform two sensitivity checks: (1) excluding English 101 and Math 227 because they were more likely to be affected by the statewide legislation regarding placement into developmental education classes implemented in 2019; (2) expanding analysis to the 11 rather than five most heavily enrolled courses.

*Research Question 3*

*Outcomes and Sample.* Research Question 3 considers the connection between online course taking in the fall and spring semesters. For this analysis, we limit our sample to FTIC students who took any online courses in the fall term to isolate the impact of taking online courses for the first time in LACCD; for comparisons of fall and spring semesters, we limit the sample further to those students who were enrolled in both semesters. Finally, for analyses of online credits earned and GPA in the spring term, we limit the sample to students who enrolled in online courses in the fall and spring. As with our first research question, our GPA analyses include only students in graded courses, excluding pass/fail enrollments. When examining persistence, we omit students who completed their credentials in fall or those who have completion records but aren't enrolled in spring. Our outcomes are: 1) whether the student took courses online in the spring, 2) number of

[11] While our preferred specification includes clustering standard errors at the course level, there are too few clusters to reliably estimate the variance-covariance matrix. As such we cluster at the student-level. Campus and course fixed effects account for most higher-level covariance, while student-level clustering provides appropriate standard errors given the insufficient number of courses for reliable variance-covariance matrix estimation (Abadie et al., 2017).

hours taken online in the spring, 3) number of hours earned online in the spring, and 4) GPA in online courses in the spring.

*Analytic Approach for RQ 3:* We estimate a descriptive linear model to understand how student performance in online courses in one term leads to changes in their course-taking behavior and outcomes the following term, as shown in Equation 7.

$$Y_i = \alpha + \beta OnlinePerformance_{itj} + \delta X_{it} + \boldsymbol{\tau}_j + \boldsymbol{\lambda}_t + \varepsilon_i \quad (7)$$

For these analyses $\mathrm{Y_i}$ is, in turn, indicators for our outcomes described above. $OnlinePerformance_{itj}$ indicates either the GPA or the number of credits student *i* earned in their online courses during the fall term *t* at campus *j*. We again control for student background characteristics as described above ($X_{it}$). For the analyses examining the impact of performance on online credit hours earned and online GPA in the spring term, we additionally include the number of total hours taken in both the fall and spring terms, as well as the number of online hours taken in the spring term to control for changes in course load. Additionally, to ensure we are specifically measuring the persistence of GPA in online courses rather than just the general consistency of a student's grades across terms, our analysis includes fall term in-person class GPA as a control variable when examining GPA outcomes. We include campus and year fixed effects and cluster standard errors by student. We also explore whether effects vary based on students' prior performance in online courses by substituting a continuous measure of GPA with a binary indicator of whether students obtained a GPA above or below 2.0 in their online courses for our predictor of interest.

## Results

*The Impact of Attempting Credits Online on Academic Outcomes (RQs 1, 1a, 1b, and 1c)*

Our findings suggest that increased online course participation leads to slightly worse academic outcomes for students. Table 4 reports the estimated effects from our propensity-weighted models for Research Questions 1, 1a, and 1b showing the effects of fall semester online course-taking on three academic outcomes: (1) term GPA, (2) credits earned in the fall semester and (3) persistence to the spring semester.

Table 4 Row 1 shows the estimated aggregated effect of attempting any credits online, with negative and significant effects on two of these three outcomes pre-pandemic (credits earned and persistence) and post-pandemic (GPA and persistence). Our estimates indicate that attempting any credits online decreased students' likelihood of persisting to the next term in the pre- and post-pandemic periods by 2-5 percentage points ($p<0.001$), decreased term GPA by 0.07 points ($p<0.001$) post-pandemic, and decreased credits earned by 0.12 credits ($p<0.001$) pre-pandemic. Notably, the difference in pre- and post-pandemic estimates for credits earned was statistically significant. Shifts in grade distributions between learning formats may explain the observed GPA changes. Before the pandemic, online students were 3 percentage points more likely to receive F s than in-person students. This disparity increased after the pandemic. The share of students earning Fs in online courses was 4 percentage points higher than among students in in-person courses, while the share of students earning As was 4 percentage points lower among students in online courses than in in-person courses—a pattern that likely contributes to the overall post-pandemic grade decline.

Table 4 Row 2 refines these estimates to assess how the effects of attempting credits online vary by the share of total credits a student attempts online in a term. These estimates suggest conspicuously negative and significant effects of taking all courses online on each of the three academic outcomes we consider. We find that attempting 100 percent of credits online leads, on average, to a 0.12 point decrease in GPA, a 0.05 decrease in credits earned, and a 6 percentage point decrease in students' likelihood of persisting. By contrast, we find some evidence that taking some, but not all courses online may improve academic outcomes, including significant and positive estimates of the effects of taking either 1-29 percent or 60-99 percent of credits online on term GPA and credits earned. This suggests that the negative effects of attempting any credits online are largely driven by students who exclusively took online courses.

Table 4 Row 3 presents the estimated effect of course modalities on academic outcomes, distinguishing between taking (1) only asynchronous; (2) only synchronous: (3) a combination of asynchronous and synchronous online courses. We find statistically significant and negative effects for each grouping of courses on all three academic outcomes, except for an insignificant estimate of the impact of asynchronous courses on credits earned. Interestingly, we find that estimated effects are most detrimental when courses are taken synchronously, followed by taking both synchronous and asynchronous courses. This suggests that synchronous courses may be driving the negative outcomes we observe for those taking both types of online courses, as well as our overall estimated effects. Table A.3 in the Appendix provides results for extensions of these analyses to annual outcomes, which are largely similar to the results in Table 4.

Table 5 refines the estimates from Table 4 on a year-by-year basis. Our results suggest that the negative impact of online course taking on student GPA was greatest in 2021-2022 and 2023-2024, while the negative impact on credit accumulation was greatest in the pre-COVID period. Interestingly, the negative impact of online course taking on persistence remained relatively unchanged in the first two years after the pandemic (3 percentage point decline) before increasing in the 2023-2024 school year (6 percentage point decline). These findings suggest that greater institutional experience with online courses did not necessarily improve GPA and persistence outcomes.

Table 6 presents results from descriptive analyses examining the differential relationship between online coursework and academic outcomes across student populations. We estimate that online courses have a negative relationship with two of the three academic outcomes for three subgroups: Older (at least 24 years of age), continuing (those who have enrolled in LACCD in prior terms), and students with lower (below 2.0) past GPA's.[12] By contrast, we find generally a positive relationship between online course enrollment on academic outcomes for FTIC students. We also find that prior academic performance moderates future performance, as the relationship between attempting credits online and students' outcomes is positive for those with prior GPAs above 2.0.

*Sensitivity analyses for Questions 1, 1a, and 1b.* Table 7 provides results from our sensitivity analyses, which exclude developmental education courses and students who took more than a full-time course load. These extensions have little effect on the estimates reported in Table 4. By contrast, we find that effect sizes increase (e.g. are more adverse) when including CTE courses, in many cases almost doubling from the main analysis, but this result is natural given that CTE courses have higher pass rates and are more likely to be in-person, which would tend to bias results towards negative findings for online coursework.

*Course-Level Impacts of Online Course Taking (RQs 2, 2a)*

At the course level, we also find that the online format yields worse outcomes on average though with some suggestion that these effects have diminished in the post-COVID period (particularly for the course completion outcome). Table 8 Row 1 reports the estimated effects remote instruction on performance in the five most heavily enrolled courses at LACCD. We find negative and significant effects of taking a course online on completing the course (2-4 percentage points less likely; $p<0.001$) and on passing the course conditional on completion (2-3 percentage points less likely; $p<0.001$), but essentially no effect on the probability of receiving a grade of A or B conditional on completing the course.

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[12] It is important to remind readers that the dependent variable of interest is continuous for these models (number of credits attempted online) rather than binary as in the analyses presented in Table 4. Further, students under 20 and FTIC students are more likely to take at least some courses in-person; therefore, it is difficult to fully disentangle heterogeneity by dosage of online course taking from heterogeneity by age.

Table 8, Rows 2 through 4 report the estimated effects of online courses on performance for courses in each of three subject areas. We find negative and significant effects for taking humanities courses online on all three outcomes, with similarly sized effects both before and after the pandemic. By contrast, we find changes over time for courses in social sciences and STEM. We estimate that attempting STEM courses online had a negative and significant effect on the likelihood of course completion prior to the pandemic, but a positive and significant effect on the probability of passing the course and receiving an A or B after the pandemic. Similarly, we estimate that attempting Social Science courses online had a negative and significant effect on the likelihood of course completion and passing the course conditional on completion, prior to the pandemic, but a negative and significant effect on course completion after the pandemic.

*Sensitivity analyses for Research Question 2.* Table 9 provides results from two sensitivity analyses for Research Questions 2, first reducing the set of courses from five to three by excluding gateway courses (Math 227 and English 101), and then by expanding the set to the 11 most heavily enrolled courses at LACCD. We find generally similar results in terms of sign, effect size, and significance of estimated effects for these alternate samples as in the original sample. This indicates that results from the main model are not biased by the inclusion of gateway courses that may include co-requisite support or unique characteristics of the top five most heavily enrolled courses.

*Performance in Online Courses and Subsequent Academic Achievement (RQ 3)*

We find a positive relationship between past and future performance in online courses. Table 10 reports the results from linear regressions using past performance to predict future performance and course taking behaviors. We find positive and significant relationships in nearly every case. Students who either achieved a higher GPA or earned a greater number of credits in fall semester online courses were, on average, more likely to take more online courses, earn more credits from online courses, and achieve higher GPAs in online courses in the spring semester. These estimated relationships show a considerable degree of persistence in performance: each additional GPA point earned in online courses is associated with a 0.48 to 0.55-point increase in next term online GPA, while each additional credit hour earned online in the fall term is associated with a 0.56 to 0.58 increase in credits earned in online courses in the next semester. There is a slightly stronger correlation between past and future performance in online than in-person courses. Pre-pandemic, current term GPA in online courses had a 0.54 correlation with next-term GPA in online courses; this increased to 0.59 post-pandemic. Pre-pandemic, current-term GPA in in-person courses had a 0.49 correlation with next-term GPA in in-person courses, which fell to 0.40 post-pandemic. Further, our analyses reveal statistically significant differences between pre-pandemic and post-pandemic periods when using online GPA as a predictor of academic outcomes. This suggests that while current performance predicts future performance for all students on average, online course performance is particularly enduring over time.

The predictive power of past performance may differ based on a student's success in online courses. To explore this, we conducted subgroup analyses of the relationship between online GPA in the fall term and subsequent term outcomes for students with GPAs below and above 2.0. Table 10 shows that the influence of online GPA was more substantial for those with online GPAs under 2.0, suggesting that students who have previously performed less well may face a steeper trajectory to improved performance in online courses. One interesting feature of the subgroup results is that the estimated effect of a student's GPA for fall term online courses was significantly more predictive of spring term online enrollment (number of credits) after the pandemic than before that. This comparison suggests that students are gaining awareness that online courses may be a better match for some than others and are using their fall semester experiences and grades to guide their future choices.

**Limitations**

This study has several limitations. First, inconsistencies in data coding during the 2019-2020 and 2020-2021 school years prevented us from evaluating the impact of distance education on student outcomes for these years. Additionally, although we could identify asynchronous courses, we could not distinguish between synchronous, hybrid, and HyFlex course formats. This limitation hindered our ability to assess the varying effects of these modalities on student success. Our data did not allow us to control for prior academic performance within our combined sample of FTIC and continuing students, as high school-level academic information (such as high school GPA) was missing for large shares of the sample. Further, due to data constraints, we could not account for students' previous experience with online courses, making it difficult to isolate the impact of prior online learning experience on outcomes in current online courses within LACCD. Despite these limitations, the study's findings still provide rigorous evidence of not only the course-level impacts of online coursework, but also the effects by online dosage and modality.

**Discussion**

Our results exemplify the continuing tension between the recent expansions of online course options at community colleges and the well-established finding that students tend to perform less well online than with in-person course delivery. With this in mind, Los Angeles Community College District (LACCD) is especially notable because of its considerable investments in professional development and technological improvements to increase student access and attempt to improve the quality of online instruction.

Our research identifies both benefits and drawbacks associated with the availability of online course options. On the positive side, students enrolled in online classes tend to attempt an average of approximately 1 more credit per semester than those taking only in-person courses. Moreover, students who once left their studies and later returned were more likely to enroll in all their credits online than those with uninterrupted enrollment. This implies that online education could improve access to higher education by enabling students to take more courses and may provide returning students with greater flexibility in how they pursue their education. We also find that the negative effects of online course taking on students' credit accumulation were attenuated in the years following the COVID-19 pandemic. This suggests that LACCD's historic investments in faculty development, student technological access, and general exposure to distance education modalities may have yielded improved student outcomes.

On the negative side, consistent with the prior literature as described above (e.g. Bettinger & Loeb, 2017; Bettinger et al., 2017; Hart et al., 2018; Xu & Jaggars, 2013, 2014), we find evidence of the negative impacts of online course modalities on student academic outcomes. First, our analyses show that students taking online courses post-pandemic had slightly lower GPAs compared to those attending in-person. Second, we find an enduring, negative impact of distance education on student persistence. This effect has remained consistent or worsened over time, decreasing the likelihood of students continuing to the next term by 4.5 percentage points, translating to roughly 3,000 fewer students persisting from fall to spring each year.

Although our findings confirm that students in online courses generally experience less favorable outcomes compared to those in traditional in-person settings, the performance gap observed at LACCD is narrower than previous research has documented. Notably, despite the substantial post-pandemic expansion of online course enrollment, we found little evidence of the expected negative selection effect, where the larger, more diverse group of students accessing online education might be less suited to the format than the smaller pre-pandemic cohort. This contradicts typical patterns in educational access expansion, where broadening participation to include academically vulnerable populations (as seen with initiatives like wider SAT testing) often results in declining overall performance metrics (Clayton & Worsham, 2024). Such expansion, in our case, represents a valuable compromise, enabling credit attainment for students who might otherwise have no pathway to academic credentials. Our results suggest an unexpected outcome: the increasing popularity and wider adoption of online courses across diverse student populations has not corresponded with large declines in short-term academic performance among this expanded group of distance learners, challenging assumptions about the relationship between broadened access and educational outcomes.

Beyond these general findings, several more targeted results stand out. First, we find that the effects of online course taking vary based on the proportion of credits taken online by a student. Again, consistent with prior research (Barrow et al., 2024), as shown in Table 7, we find that a negative and statistically significant decline in academic outcomes (GPA, credits earned, persistence to the next semester) for taking all credits online as compared to those taking all credits in person. We also find that students who take a mix of in-person and online courses earn more credits, have higher GPAs, and are more likely to persist than those taking solely online courses. This suggests that students who have anchoring in-person courses but take enough credits online to develop aligned skills, such as self-regulation and time management, may get the "best of both worlds." Additionally, taking a mix of in-person and online courses may provide students with schedule flexibility that better accommodates their personal circumstances, potentially contributing to improved academic performance

Second, we find that the effects of asynchronous courses tend to be better than the effects of attempting synchronous courses. This aligns with qualitative work in the district, which suggests that when faculty teach asynchronously they completely redesign their courses to facilitate student engagement and learning in an asynchronous environment, while synchronous courses taught on Zoom try to more directly replicate in-person learning but with more distractions, less engagement, and weaker connections between students and instructors (Swanson et al., 2023). We did not have sufficient evidence to evaluate more innovative modalities such as hybrid and HyFlex courses; initial qualitative findings suggest that these modalities may be particularly burdensome for faculty (Swanson et al., 2023).

Third, we also find that the effects of online courses vary by course subject. Reflecting prior work (Hart et al., 2018), we find that across the humanities, social sciences, and STEM fields, switching a course to an online modality prior to the pandemic reduced the likelihood that students would complete the course. After the pandemic, many of the negative impacts of the online modality were attenuated in all disciplines and were largely eliminated or reversed in the social sciences and STEM fields. This was particularly pronounced for STEM courses, where there was a significant increase in the likelihood students would pass the course (two percentage points) and earn an A or B (five percentage points) in the post-COVID years. One possible explanation for these results is that, after the pandemic, online courses have been more common for STEM than for humanities classes, which may have allowed STEM faculty members to gain experience and improve their online teaching skills. This suggests that colleges may want to vary the extent to which distance education courses are offered across subjects and/or focus additional efforts on the suitability of different types of course material to the online format.

Finally, we offer descriptive evidence on the extent to which students' initial experiences in online courses predict future behavior. We find that students who do better in their online courses tend to continue taking online courses in the next term and have better academic results on average when they do so. For example, consider a student enrolled in four online courses of three credit hours each. If this student achieves one letter grade higher in just one of these courses, they will experience approximately a one-third point increase in their online course GPA during the subsequent term. This suggests that while some students thrive in online environments, others consistently struggle. Identifying the distinguishing characteristics between these groups, potentially factors like previous online learning experience or specific digital study skills, would be valuable and help improve academic advising. Additional research may also help institutions design and test interventions that promote the development of relevant skills, potentially mitigating the adverse effects we estimate for students taking online courses.

An overarching theme of this work and other literature on distance education is that online teaching requires a combination of care and skill (Kofoed et al., 2021; Swanson et al., 2023). Though expedient, the default plan of transferring materials and teaching approaches directly from in-person to the online format may lead to relatively poor academic outcomes. Further, our results suggest that technological investment and teacher training may improve the quality of online courses so that they work at least as well, if not better, than in-person courses for subgroups of students and for course topics that are well-matched to that format. While we do not view online education as a panacea, our results suggest that community colleges can make valuable use of online courses in the challenging post-COVID landscape.

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## Tables

Table 1
Descriptive Statistics

| | Pre-Covid | | | Post-Covid | | |
|---|---|---|---|---|---|---|
| | All LACCD | Continuing | FTIC | All LACCD | Continuing | FTIC |
| | Mean (SD) | | | | | |
| Fall GPA | 2.42 | 2.48 | 2.19 | 2.47 | 2.59 | 2.03 |
| | (1.31) | (1.30) | (1.31) | (1.42) | (1.38) | (1.47) |
| N Credits Earned in Fall | 5.47 | 5.25 | 6.41 | 5.16 | 5.01 | 5.70 |
| | (4.36) | (4.21) | (4.83) | (4.44) | (4.24) | (5.06) |
| Enrolled in the Spring | 0.70 | 0.69 | 0.72 | 0.66 | 0.66 | 0.69 |
| | (0.46) | (0.46) | (0.45) | (0.47) | (0.47) | (0.46) |
| N Credits Attempted Online in Fall | 1.29 | 1.38 | 0.92 | 5.58 | 5.56 | 5.67 |
| | (2.44) | (2.50) | (2.11) | (4.08) | (3.98) | (4.43) |
| N Credits Attempted Async in Fall | 1.29 | 1.38 | 0.92 | 4.15 | 4.20 | 3.99 |
| | (2.44) | (2.50) | (2.11) | (3.72) | (3.70) | (3.81) |
| N Credits Attempted Sync in Fall | 0.00 | 0.00 | 0.00 | 1.43 | 1.37 | 1.67 |
| | (0.00) | (0.00) | (0.00) | (2.56) | (2.45) | (2.90) |
| N Non-CTE Credits Attempted in Fall | 7.93 | 7.53 | 9.61 | 7.67 | 7.23 | 9.28 |
| | (4.00) | (3.88) | (4.04) | (4.08) | (3.95) | (4.15) |
| N CTE Credits Attempted in Fall | 1.28 | 1.33 | 1.06 | 1.55 | 1.57 | 1.49 |
| | (2.37) | (2.44) | (2.06) | (2.66) | (2.71) | (2.45) |
| Received Pell Grant or BoG Grant | 0.67 | 0.66 | 0.72 | 0.62 | 0.59 | 0.73 |
| | (0.47) | (0.48) | (0.45) | (0.48) | (0.49) | (0.44) |
| LACP Participant | 0.07 | 0.02 | 0.26 | 0.19 | 0.15 | 0.36 |
| | (0.25) | (0.14) | (0.44) | (0.40) | (0.36) | (0.48) |
| Male | 0.42 | 0.41 | 0.48 | 0.42 | 0.40 | 0.50 |
| | (0.49) | (0.49) | (0.50) | (0.49) | (0.49) | (0.50) |
| Female | 0.58 | 0.59 | 0.52 | 0.57 | 0.59 | 0.49 |
| | (0.49) | (0.49) | (0.50) | (0.49) | (0.49) | (0.50) |
| Non-Binary | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 |
| | (0.00) | (0.00) | (0.00) | (0.07) | (0.06) | (0.09) |
| Hispanic | 0.64 | 0.63 | 0.69 | 0.64 | 0.63 | 0.67 |
| | (0.48) | (0.48) | (0.46) | (0.48) | (0.48) | (0.47) |
| White | 0.14 | 0.15 | 0.12 | 0.16 | 0.15 | 0.17 |
| | (0.35) | (0.36) | (0.32) | (0.36) | (0.36) | (0.38) |
| Black | 0.10 | 0.10 | 0.09 | 0.09 | 0.09 | 0.07 |
| | (0.29) | (0.30) | (0.28) | (0.28) | (0.29) | (0.25) |
| Asian | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 | 0.04 |
| | (0.25) | (0.26) | (0.23) | (0.23) | (0.24) | (0.20) |
| Filipino | 0.03 | 0.03 | 0.02 | 0.03 | 0.03 | 0.02 |
| | (0.16) | (0.16) | (0.15) | (0.16) | (0.16) | (0.15) |
| Pacific Islander | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.05) | (0.04) | (0.04) | (0.04) |
| American Indian | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Multiethnic | 0.02 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 |
| | (0.15) | (0.15) | (0.14) | (0.16) | (0.17) | (0.16) |
| Under 20 | 0.25 | 0.14 | 0.70 | 0.28 | 0.15 | 0.75 |
| | (0.43) | (0.35) | (0.46) | (0.45) | (0.36) | (0.43) |
| 20-24 | 0.37 | 0.42 | 0.15 | 0.32 | 0.38 | 0.09 |
| | (0.48) | (0.49) | (0.35) | (0.47) | (0.49) | (0.29) |
| 25-34 | 0.24 | 0.28 | 0.09 | 0.24 | 0.28 | 0.07 |
| | (0.43) | (0.45) | (0.29) | (0.43) | (0.45) | (0.26) |
| 35-54 | 0.11 | 0.13 | 0.05 | 0.13 | 0.15 | 0.06 |
| | (0.32) | (0.34) | (0.21) | (0.34) | (0.35) | (0.25) |

| | | | | | | |
|---|---|---|---|---|---|---|
| 55 and Over | 0.03 | 0.03 | 0.01 | 0.03 | 0.03 | 0.02 |
| | (0.17) | (0.18) | (0.11) | (0.17) | (0.18) | (0.14) |
| FTIC | 0.19 | | | 0.21 | | |
| | (0.39) | | | (0.41) | | |
| N | 183,840 | 148,510 | 35,330 | 190,741 | 149,796 | 40,945 |

Table 2
Descriptive Statistics of Term-Level Analysis Sample by Dosage of Online Course Taking

| | All In-Person | Any Online | Only Synchronous (Post-Covid) | Only Asynchronous (Post-Covid) | 1-29% Credits Online (Post-Covid) | 30-59% Credits Online (Post-Covid) | 60-99% Credits Online (Post-Covid) | 100% Credits Online (Post-Covid) |
|---|---|---|---|---|---|---|---|---|
| | Mean (SD) | | | | | | | |
| Fall GPA | 2.39 | 2.49 | 2.38 | 2.51 | 2.46 | 2.39 | 2.56 | 2.49 |
| | (1.34) | (1.39) | (1.45) | (1.43) | (1.26) | (1.34) | (1.27) | (1.46) |
| N Credits Earned in Fall | 5.00 | 5.55 | 3.98 | 5.07 | 8.73 | 6.77 | 8.24 | 4.59 |
| | (4.19) | (4.54) | (3.70) | (4.37) | (4.76) | (4.59) | (4.81) | (4.14) |
| Enrolled in the Spring | 0.68 | 0.68 | 0.60 | 0.65 | 0.85 | 0.77 | 0.81 | 0.62 |
| | (0.46) | (0.47) | (0.49) | (0.48) | (0.36) | (0.42) | (0.39) | (0.49) |
| N Credits Attempted Online in Fall | 0.00 | 6.10 | 5.09 | 5.85 | 2.79 | 4.51 | 8.43 | 6.85 |
| | (0.00) | (3.48) | (2.58) | (3.30) | (0.83) | (1.73) | (2.72) | (3.79) |
| N Credits Attempted Async in Fall | 0.00 | 4.82 | 0.00 | 5.85 | 2.31 | 3.51 | 6.49 | 5.02 |
| | (0.00) | (3.34) | (0.00) | (3.30) | (1.29) | (2.21) | (3.42) | (3.71) |
| N Credits Attempted Sync in Fall | 0.00 | 1.28 | 5.09 | 0.00 | 0.48 | 1.00 | 1.94 | 1.83 |
| | (0.00) | (2.46) | (2.58) | (0.00) | (1.11) | (1.79) | (2.74) | (2.84) |
| N Non-CTE Credits Attempted in Fall | 7.37 | 8.13 | 6.42 | 7.38 | 12.35 | 10.06 | 11.62 | 6.85 |
| | (3.88) | (4.13) | (3.39) | (4.03) | (2.70) | (3.28) | (3.26) | (3.79) |
| N CTE Credits Attempted in Fall | 1.29 | 1.51 | 1.40 | 1.72 | 0.82 | 1.35 | 1.17 | 1.68 |
| | (2.40) | (2.61) | (2.58) | (2.81) | (1.82) | (2.26) | (2.05) | (2.82) |
| Received Pell Grant or BoG Grant | 0.64 | 0.65 | 0.57 | 0.63 | 0.70 | 0.67 | 0.70 | 0.62 |
| | (0.48) | (0.48) | (0.50) | (0.48) | (0.46) | (0.47) | (0.46) | (0.49) |
| LACP Participant | 0.09 | 0.16 | 0.15 | 0.18 | 0.43 | 0.32 | 0.34 | 0.14 |
| | (0.29) | (0.37) | (0.36) | (0.39) | (0.50) | (0.47) | (0.47) | (0.35) |
| Male | 0.46 | 0.40 | 0.45 | 0.40 | 0.51 | 0.47 | 0.47 | 0.38 |
| | (0.50) | (0.49) | (0.50) | (0.49) | (0.50) | (0.50) | (0.50) | (0.49) |
| Female | 0.54 | 0.60 | 0.55 | 0.60 | 0.48 | 0.52 | 0.52 | 0.61 |
| | (0.50) | (0.49) | (0.50) | (0.49) | (0.50) | (0.50) | (0.50) | (0.49) |
| Non-Binary | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 |
| | (0.03) | (0.06) | (0.06) | (0.06) | (0.09) | (0.08) | (0.08) | (0.05) |
| Hispanic | 0.67 | 0.62 | 0.65 | 0.62 | 0.71 | 0.70 | 0.64 | 0.61 |
| | (0.47) | (0.49) | (0.48) | (0.48) | (0.45) | (0.46) | (0.48) | (0.49) |
| White | 0.13 | 0.16 | 0.14 | 0.17 | 0.12 | 0.11 | 0.14 | 0.18 |
| | (0.34) | (0.37) | (0.35) | (0.38) | (0.32) | (0.32) | (0.34) | (0.38) |
| Black | 0.08 | 0.10 | 0.09 | 0.09 | 0.05 | 0.07 | 0.09 | 0.10 |
| | (0.27) | (0.30) | (0.28) | (0.29) | (0.21) | (0.25) | (0.29) | (0.30) |
| Asian | 0.07 | 0.06 | 0.07 | 0.05 | 0.06 | 0.06 | 0.06 | 0.06 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.25) | (0.24) | (0.25) | (0.23) | (0.24) | (0.23) | (0.23) | (0.23) |
| Filipino | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | (0.15) | (0.16) | (0.16) | (0.16) | (0.17) | (0.17) | (0.17) | (0.16) |
| Pacific Islander | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.03) | (0.04) | (0.03) | (0.04) | (0.05) | (0.04) |
| American Indian | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.05) | (0.04) | (0.04) | (0.04) |
| Multiethnic | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | (0.14) | (0.17) | (0.16) | (0.17) | (0.17) | (0.17) | (0.18) | (0.16) |
| Under 20 | 0.28 | 0.25 | 0.24 | 0.25 | 0.62 | 0.46 | 0.47 | 0.20 |
| | (0.45) | (0.44) | (0.43) | (0.43) | (0.49) | (0.50) | (0.50) | (0.40) |
| 20-24 | 0.36 | 0.33 | 0.32 | 0.32 | 0.26 | 0.33 | 0.33 | 0.32 |
| | (0.48) | (0.47) | (0.47) | (0.47) | (0.44) | (0.47) | (0.47) | (0.47) |
| 25-34 | 0.22 | 0.25 | 0.27 | 0.25 | 0.09 | 0.15 | 0.13 | 0.28 |
| | (0.41) | (0.43) | (0.45) | (0.43) | (0.29) | (0.36) | (0.34) | (0.45) |
| 35-54 | 0.11 | 0.13 | 0.14 | 0.15 | 0.03 | 0.05 | 0.05 | 0.17 |
| | (0.31) | (0.34) | (0.35) | (0.35) | (0.18) | (0.22) | (0.22) | (0.37) |
| 55 and Over | 0.04 | 0.03 | 0.03 | 0.03 | 0.01 | 0.01 | 0.01 | 0.04 |
| | (0.19) | (0.16) | (0.17) | (0.18) | (0.08) | (0.10) | (0.12) | (0.19) |
| FTIC | 0.22 | 0.19 | 0.20 | 0.19 | 0.48 | 0.33 | 0.30 | 0.15 |
| | (0.42) | (0.39) | (0.40) | (0.39) | (0.50) | (0.47) | (0.46) | (0.36) |
| N | 161,079 | 213,502 | 23,419 | 105,873 | 5,469 | 21,230 | 17,199 | 118,110 |

Table 3
Results of Joint Test of Significance

| | Omnibus Test P-Value | | Average Percent Standardized Bias | |
|---|---|---|---|---|
| | Pre-Weighting | Post-Weighting | Pre-Weighting | Post-Weighting |
| | Scheme 1 | | | |
| FTIC 1-29% Hours Online Post-COVID | <0.001 | >.05 | 13.87% | 0.59% |
| FTIC 30-59% Hours Online Post-COVID | <0.001 | >.05 | 10.35% | 1.07% |
| FTIC 60-99% Hours Online Post-COVID | <0.001 | >.05 | 14.02% | 1.72% |
| FTIC 100% Hours Online Post-COVID | <0.001 | <0.01 | 9.63% | 1.54% |
| Continuing 1-29% Hours Online Post-COVID | <0.001 | >.05 | 16.69% | 0.93% |
| Continuing 30-59% Hours Online Post-COVID | <0.001 | >.05 | 9.93% | 0.97% |
| Continuing 60-100% Hours Online Post-COVID | <0.001 | <0.01 | 15.08 | 2.09% |
| Continuing 100% Hours Online Post-COVID | <0.001 | <0.001 | 9.21% | 1.12% |
| | Scheme 2 | | | |
| Pre-COVID FTIC | <0.001 | >.05 | 9.06% | 0.53% |
| Post-COVID FTIC | <0.001 | >.05 | 8.97% | 1.04% |
| Pre-COVID Continuing | <0.001 | >.05 | 9.00% | 0.57% |
| Post-COVID Continuing | <0.001 | <0.01 | 8.44% | 1.18% |
| | Scheme 3 | | | |
| Post-COVID FTIC Async Only | <0.001 | >.05 | 11.00% | 1.31% |
| Post-COVID FTIC Sync Only | <0.001 | >.05 | 8.66% | 0.38% |
| Post-COVID FTIC Both | <0.001 | <0.01 | 10.79% | 1.45% |
| Post-COVID Continuing Async Only | <0.001 | <0.01 | 8.50% | 1.16% |
| Post-COVID Continuing Sync Only | <0.001 | >.05 | 8.37% | 0.32% |
| Post-COVID Continuing Both | <0.001 | <0.01 | 13.36% | 2.02% |

Table 4
Total Marginal Effect of Attempting Credits Online in the Fall Term

| | | Term GPA | | Credits Earned | | Enrolled in the Spring | |
|---|---|---|---|---|---|---|---|
| Row Number | Predictor | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| 1 | Took Any Course Online | 0.004 | -0.066*** | -0.122***+ | -0.033 | -0.020*** | -0.045*** |
| | | (0.008) | (0.012) | (0.018) | (0.026) | (0.002) | (0.003) |
| | N | 331,331 | | 374,384 | | 362,713 | |
| 2 | 1-29% hours online | | 0.107** | | 0.278*** | | 0.005 |
| | | | (0.025) | | (0.078) | | (0.007) |
| | N | | 29,441 | | 34,046 | | 33,161 |
| | 30-59% hours online | | -0.022 | | -0.080 | | 0.002 |
| | | | (0.015) | | (0.044) | | (0.004) |
| | N | | 44,312 | | 49,902 | | 48,582 |
| | 60-99% hours online | | 0.125*** | | 0.170** | | 0.004 |
| | | | (0.019) | | (0.060) | | (0.006) |
| | N | | 40,913 | | 45,905 | | 44,546 |
| | 100% hours online | | -0.119*** | | -0.050* | | -0.062*** |
| | | | (0.012) | | (0.023) | | (0.004) |
| | N | | 126,723 | | 146,801 | | 140,683 |
| 3 | Took Only Asynchronous Courses | | -0.057*** | | 0.025 | | -0.049*** |
| | | | (0.012) | | (0.026) | | (0.004) |
| | N | | 118,476 | | 134,442 | | 129,061 |
| | Took Only Synchronous Courses | | -0.115*** | | -0.158*** | | -0.047*** |
| | | | (0.016) | | (0.029) | | (0.005) |
| | N | | 43,380 | | 52,116 | | 50,548 |
| | Took Both | | -0.069*** | | -0.139* | | -0.016** |
| | | | (0.019) | | (0.055) | | (0.005) |
| | N | | 55,265 | | 61,386 | | 59,429 |

*Note*. * p<0.05, ** p<0.01, *** p<0.001 + denotes that the pre- and post-COVID point estimates have a statistically significant difference. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for credits attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

Table 5

Total Marginal Effect of Credits Attempted Online in Fall Term, by Year

| Method | | AYs 2017/18-2018/19 | AY 2021-2022 | AY 2022-2023 | AY 2023-2024 |
|---|---|---|---|---|---|
| | | Marginal Effect (SE) | | | |
| Matching | Term GPA | 0.004 | -0.160*** | -0.000 | -0.086*** |
| | | (0.008) | (0.030) | (0.018) | (0.016) |
| | N | 162,561 | 55,867 | 54,950 | 57,954 |
| | Hours Earned (term) | -0.127*** | -0.104 | 0.030 | -0.058 |
| | | (0.018) | (0.053) | (0.040) | (0.034) |
| | N | 183,726 | 63,806 | 61,839 | 65,013 |
| | Enrolled in the Spring | -0.021*** | -0.033*** | -0.032*** | -0.062*** |
| | | (0.002) | (0.009) | (0.005) | (0.005) |
| | N | 179,405 | 61,115 | 59,511 | 62,682 |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. Sample includes FTIC and continuing students. Estimates are the average marginal effect for credits attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

Table 6
Total Marginal Effect of Credits Attempted Online in Fall Term, by Student Population

| | Enrollment Status | | Pell/BoG (FTIC only) | | Age (FTIC Only) | | Fall GPA (FTIC only) | |
|---|---|---|---|---|---|---|---|---|
| Outcome | FTIC | Continuing | No Pell/BoG | Pell/BoG | >24 | <=24 | <2.0 | >2.0 |
| | Marginal Effect (SE) | | | | | | | |
| Term GPA | 0.005* | -0.003* | -0.002 | 0.008*** | -0.012+ | 0.008*** | -0.023***+ | 0.004 |
| | (0.002) | (0.001) | (0.003) | (0.002) | (0.006) | (0.00) | (0.004) | (0.002) |
| N | 36,621 | 132,223 | 36,621 | | 36,621 | | 23,938 | |
| Hours Earned (term) | 0.019** | 0.007 | 0.026** | 0.017* | -0.097***+ | 0.033*** | -0.165***+ | 0.079*** |
| | (0.006) | (0.004) | (0.010) | (0.007) | (0.015) | (0.006) | (0.011) | (0.007) |
| N | 40,942 | 149,791 | 40,942 | | 40,942 | | 25,593 | |
| Enrolled in the Spring | -0.002*** | -0.008*** | 0.001 | -0.004*** | -0.006*** | -0.002*** | | |
| | (0.001) | (0.000) | (0.001) | (0.001) | (0.002) | (0.001) | | |
| N | 40,682 | 142,697 | 40,682 | | 40,682 | | | |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. + denotes that group point estimates have a statistically significant difference. Sample includes AYs 2021/22, 2022/23, 2023/24. Estimates are the average marginal effect for the number of credits attempted online for each group. Standard errors clustered at the student-level.

Table 7
Total Marginal Effect of Attempting Credits Online under Alternate Sample Constructions

| | | Term GPA | | Hours Earned | | Enrolled in the Spring | |
|---|---|---|---|---|---|---|---|
| Sensitivity Check | Predictor | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| Excluding Developmental Education | Took Any Course Online | -0.025** | -0.066*** | -0.123*** | -0.019 | -0.032*** | -0.046*** |
| | | (0.008) | (0.012) | (0.018) | (0.025) | (0.002) | (0.003) |
| | N | 323,965 | | 363,851 | | 352,296 | |
| | 1-29% hours online | | 0.107*** | | 0.294*** | | 0.003 |
| | | | (0.025) | | (0.079) | | (0.007) |
| | N | | 29,450 | | 33,811 | | 32,936 |
| | 30-59% hours online | | -0.020 | | -0.077 | | 0.000 |
| | | | (0.015) | | (0.044) | | (0.004) |
| | N | | 44,246 | | 49,524 | | 48,208 |
| | 60-99% hours online | | 0.128*** | | 0.174** | | 0.002 |
| | | | (0.019) | | (0.060) | | (0.006) |
| | N | | 40,688 | | 45,378 | | 44,034 |
| | 100% hours online | | -0.116*** | | -0.029 | | -0.062*** |
| | | | (0.013) | | (0.023) | | (0.004) |
| | N | | 125,869 | | 145,069 | | 138,987 |
| Excluding > 18 Hours | Took Any Course Online | 0.003 | -0.067*** | -0.123*** | -0.033 | -0.019*** | -0.045*** |
| | | (0.008) | (0.012) | (0.018) | (0.016) | (0.002) | (0.003) |
| | N | 329,804 | | 372,864 | | 361,249 | |
| | 1-29% hours online | | 0.107*** | | 0.280*** | | 0.005 |
| | | | (0.025) | | (0.078) | | (0.007) |
| | N | | 29,378 | | 33,983 | | 33,098 |
| | 30-59% hours online | | -0.022 | | -0.079 | | 0.002 |
| | | | (0.015) | | (0.044) | | (0.004) |
| | N | | 44,119 | | 49,709 | | 48,393 |
| | 60-99% hours online | | 0.125*** | | 0.172** | | 0.004 |
| | | | (0.019) | | (0.060) | | (0.006) |
| | N | | 40,591 | | 45,579 | | 44,229 |
| | 100% hours online | | -0.119*** | | -0.051* | | -0.062*** |
| | | | (0.012) | | (0.023) | | (0.004) |
| | N | | 126,306 | | 146,379 | | 140,288 |
| Including CTE Courses | Took Any Course Online | -0.025*** | -0.131*** | -0.321*** | -0.454*** | -0.023*** | -0.063*** |
| | | (0.007) | (0.009) | (0.018) | (0.025) | (0.002) | (0.003) |
| | N | 415,965 | | 461,683 | | 444,341 | |
| | 1-29% hours online | | -0.002 | | -0.110 | | 0.011 |
| | | | (0.019) | | (0.066) | | (0.006) |
| | N | | 42,766 | | 48,069 | | 45,687 |
| | 30-59% hours online | | -0.090*** | | -0.453*** | | -0.000 |
| | | | (0.013) | | (0.039) | | (0.004) |
| | N | | 59,260 | | 65,700 | | 62,788 |
| | 60-99% hours online | | -0.011 | | -0.327*** | | -0.003 |
| | | | (0.016) | | (0.054) | | (0.005) |
| | N | | 57,928 | | 63,773 | | 60,764 |
| | 100% hours online | | -0.176*** | | -0.474*** | | -0.089*** |
| | | | (0.010) | | (0.022) | | (0.003) |
| | N | | 159,318 | | 180,653 | | 172,088 |

*Note.* * p<0.05, ** p<0.01, *** p<0.001. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for credits attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

Table 8
Total Marginal Effect of Online Course Attempt on Academic Outcomes

| | | Completed Course | | Passed Course | | Received A or B | |
|---|---|---|---|---|---|---|---|
| Row Number | Predictor | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| 1 | Took Course Online | -0.041***+ | -0.019*** | -0.029*** | -0.017*** | 0.000 | -0.001 |
| | | (0.003) | (0.003) | (0.004) | (0.003) | (0.004) | (0.004) |
| | N | 277,712 | | 231,084 | | 231,063 | |
| 2 | Took Humanities Course Online | -0.048***+ | -0.032*** | -0.048*** | -0.042*** | -0.027*** | -0.035*** |
| | | (0.004) | (0.003) | (0.004) | (0.004) | (0.005) | (0.004) |
| | N | 205,822 | | 171,847 | | 171,838 | |
| 3 | Took STEM Course Online | -0.053***+ | -0.006 | -0.002 | 0.020** | -0.007+ | 0.036*** |
| | | (0.008) | (0.005) | (0.009) | (0.006) | (0.010) | (0.007) |
| | N | 91,034 | | 71,956 | | 71,944 | |
| 4 | Took Social Sciences Course Online | -0.036***+ | -0.007* | -0.010* | 0.003 | 0.031*** | 0.017** |
| | | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) |
| | N | 153,024 | | 133,933 | | 133,916 | |

*Note*. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. + denotes that the pre- and post-covid point estimates have a statistically significant difference. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for a course being attempted online before and since COVID. Standard errors clustered at the student-level. N humanities students who took course online=90,249, N humanities students who took course in-person=117,937, N STEM students who took course online=38,907, N STEM students who took course in-person=52,644, N social science students who took course online=76,700, N social science students who took course in-person=77,322.

Table 9

Total Marginal Effect of Online Course Attempt on Academic Outcomes under Alternate Sample Constructions

| | Excluding math and English | | Including 11 Highest-Enrollment Courses | |
|---|---|---|---|---|
| Outcome | Pre-COVID | Post -COVID | Pre-COVID | Post -COVID |
| | Marginal Effect (SE) | | | |
| Completed Course | -0.033***+ | -0.008* | -0.045***+ | -0.019*** |
| | (0.004) | (0.003) | (0.002) | (0.002) |
| N | 148,678 | | 448,880 | |
| Passed Course (A-C, Pass) | -0.023*** | -0.016*** | -0.030***+ | -0.013*** |
| | (0.004) | (0.004) | (0.003) | (0.003) |
| N | 128,505 | | 377,736 | |
| Received A or B | 0.014** | 0.006 | -0.004 | -0.001 |
| | (0.005) | (0.005) | (0.003) | (0.003) |
| N | 128,492 | | 377,698 | |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. + denotes that the pre- and post-covid point estimates have a statistically significant difference. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for a course being attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

Table 10
Relationship between Current and Future Online Course Performance, by Academic Achievement

| Predictor | Online GPA in Fall Term | | Online GPA in Fall Term <=2.0 | | Online GPA in Fall Term >2.0 | | Credits Earned Online in Fall Term | |
|---|---|---|---|---|---|---|---|---|
| Outcome | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| | Marginal Effect (SE) | | | | | | | |
| Next Term Online Courses Taken | 0.041*** | 0.034*** | 0.037** | 0.056*** | 0.024 | 0.018*** | 0.032*** | 0.013*** |
| | (0.005) | (0.002) | (0.013) | (0.005) | (0.017) | (0.005) | (0.002) | (0.001) |
| N | 26,032 | | 10,462 | | 15,570 | | 28,353 | |
| Next Term Online Credits Taken | 0.282***+ | 0.521*** | 0.203*+ | 0.612*** | 0.155 | 0.442*** | 0.253*** | 0.252*** |
| | (0.033) | (0.020) | (0.081) | (0.052) | (0.128) | (0.065) | (0.021) | (0.009) |
| N | 26,032 | | 10,462 | | 15,570 | | 28,353 | |
| Next Term Online Credits Earned | 1.118***+ | 1.354*** | 1.076*** | 1.402*** | 1.060*** | 1.168*** | 0.576*** | 0.556*** |
| | (0.051) | (0.020) | (0.143) | (0.057) | (0.156) | (0.057) | (0.023) | (0.009) |
| N | 20,938 | | 7,731 | | 13,207 | | 22,290 | |
| Next Term Online GPA | 0.481***+ | 0.552*** | 0.398*** | 0.467*** | 0.621*** | 0.636*** | 0.183*** | 0.195*** |
| | (0.019) | (0.008) | (0.054) | (0.021) | (0.054) | (0.020) | (0.008) | (0.003) |
| N | 19,168 | | 6,578 | | 12,590 | | 20,170 | |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. + denotes that the pre- and post-covid point estimates have a statistically significant difference. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22 & 2022/23. Sample limited to FTIC students. Estimates are the average marginal effect for performance in online courses before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

## Appendix

Table A.1
Descriptive Statistics of Annual-Level Analysis Sample by Dosage of Online Course Taking

| | All In-Person | Any Online | Only Synchronous (Post-Covid) | Only Asynchronous (Post-Covid) | 1-29% Credits Online (Post-Covid) | 30-59% Credits Online (Post-Covid) | 60-99% Credits Online (Post-Covid) | 100% Credits Online (Post-Covid) |
|---|---|---|---|---|---|---|---|---|
| | Mean (SD) | | | | | | | |
| Annual GPA | 2.48 | 2.6 | 2.44 | 2.65 | 2.45 | 2.53 | 2.65 | 2.66 |
| | (1.14) | (1.17) | (1.29) | (1.21) | (1.16) | (1.17) | (1.09) | (1.21) |
| N Credits Earned in Academic Year | 10.52 | 12.12 | 7.69 | 10.85 | 14.19 | 13.09 | 16.26 | 10.74 |
| | (7.37) | (8.04) | (6.40) | (7.82) | (7.87) | (8.30) | (8.32) | (7.47) |
| Enrolled in the Following Fall | 0.72 | 0.70 | 0.65 | 0.68 | 0.79 | 0.75 | 0.75 | 0.67 |
| | (0.45) | (0.46) | (0.48) | (0.47) | (0.41) | (0.43) | (0.43) | (0.47) |
| N Credits Attempted Online in Academic Year | 0.00 | 10.28 | 6.81 | 10.31 | 3.96 | 8.17 | 15.38 | 13.62 |
| | (0.00) | (6.76) | (4.45) | (6.42) | (1.64) | (3.83) | (5.83) | (7.03) |
| N Credits Attempted Async in Academic Year | 0.00 | 8.45 | 0.00 | 10.31 | 3.16 | 6.41 | 12.31 | 10.37 |
| | (0.00) | (6.06) | (0.00) | (6.42) | (2.02) | (4.08) | (6.28) | (6.72) |
| N Credits Attempted Sync in Academic Year | 0.00 | 1.83 | 6.81 | 0.00 | 0.80 | 1.76 | 3.07 | 3.25 |
| | (0.00) | (3.55) | (4.45) | (0.00) | (1.57) | (2.69) | (4.03) | (4.46) |
| N Non-CTE Credits Attempted in Academic Year | 14.40 | 16.36 | 11.45 | 14.52 | 19.73 | 17.97 | 21.60 | 14.43 |
| | (7.44) | (7.74) | (6.61) | (7.76) | (6.04) | (7.47) | (6.41) | (7.19) |
| N CTE Credits Attempted in Academic Year | 3.56 | 4.00 | 4.65 | 4.84 | 2.88 | 3.36 | 3.03 | 4.33 |
| | (5.08) | (5.33) | (5.95) | (5.94) | (4.03) | (4.66) | (4.12) | (5.58) |
| Received Pell Grant or BoG Grant | 0.71 | 0.72 | 0.63 | 0.70 | 0.69 | 0.68 | 0.73 | 0.70 |
| | (0.46) | (0.45) | (0.48) | (0.46) | (0.46) | (0.47) | (0.44) | (0.46) |
| LACP Participant | 0.10 | 0.18 | 0.17 | 0.22 | 0.36 | 0.33 | 0.37 | 0.18 |
| | (0.30) | (0.39) | (0.38) | (0.42) | (0.48) | (0.47) | (0.48) | (0.38) |
| Male | 0.47 | 0.40 | 0.50 | 0.40 | 0.53 | 0.47 | 0.40 | 0.38 |
| | (0.50) | (0.49) | (0.50) | (0.49) | (0.50) | (0.50) | (0.49) | (0.49) |
| Female | 0.53 | 0.60 | 0.50 | 0.59 | 0.46 | 0.52 | 0.52 | 0.62 |
| | (0.50) | (0.49) | (0.50) | (0.49) | (0.50) | (0.50) | (0.50) | (0.49) |
| Non-Binary | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.00 |
| | (0.03) | (0.06) | (0.07) | (0.07) | (0.10) | (0.08) | (0.08) | (0.06) |
| Hispanic | 0.68 | 0.63 | 0.68 | 0.65 | 0.73 | 0.71 | 0.64 | 0.62 |
| | (0.46) | (0.48) | (0.47) | (0.48) | (0.44) | (0.46) | (0.48) | (0.49) |
| White | 0.13 | 0.16 | 0.13 | 0.16 | 0.11 | 0.12 | 0.15 | 0.17 |
| | (0.34) | (0.37) | (0.34) | (0.37) | (0.31) | (0.32) | (0.35) | (0.38) |
| Black | 0.07 | 0.09 | 0.07 | 0.08 | 0.04 | 0.06 | 0.09 | 0.09 |
| | (0.25) | (0.29) | (0.26) | (0.27) | (0.20) | (0.23) | (0.28) | (0.29) |
| Asian | 0.07 | 0.06 | 0.06 | 0.05 | 0.06 | 0.06 | 0.06 | 0.06 |
| | (0.25) | (0.24) | (0.25) | (0.22) | (0.24) | (0.23) | (0.24) | (0.23) |
| Filipino | 0.02 | 0.03 | 0.02 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 |
| | (0.15) | (0.16) | (0.15) | (0.15) | (0.16) | (0.17) | (0.18) | (0.16) |
| Pacific Islander | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (0.04) | (0.04) | (0.02) | (0.04) | (0.03) | (0.03) | (0.06) | (0.04) |
| American Indian | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | (0.04) | (0.04) | (0.05) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) |
| Multiethnic | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| | (0.13) | (0.16) | (0.16) | (0.17) | (0.16) | (0.17) | (0.18) | (0.16) |
| Under 20 | 0.29 | 0.30 | 0.25 | 0.30 | 0.54 | 0.45 | 0.50 | 0.24 |
| | (0.46) | (0.46) | (0.43) | (0.46) | (0.50) | (0.50) | (0.50) | (0.43) |
| 20-24 | 0.35 | 0.33 | 0.31 | 0.31 | 0.29 | 0.32 | 0.31 | 0.31 |
| | (0.48) | (0.47) | (0.46) | (0.46) | (0.46) | (0.47) | (0.46) | (0.46) |
| 25-34 | 0.21 | 0.23 | 0.26 | 0.23 | 0.11 | 0.15 | 0.12 | 0.26 |
| | (0.41) | (0.42) | (0.44) | (0.42) | (0.32) | (0.36) | (0.32) | (0.44) |
| 35-54 | 0.11 | 0.12 | 0.14 | 0.14 | 0.04 | 0.06 | 0.05 | 0.15 |
| | (0.31) | (0.32) | (0.35) | (0.34) | (0.20) | (0.24) | (0.22) | (0.36) |
| 55 and Over | 0.04 | 0.03 | 0.03 | 0.03 | 0.01 | 0.01 | 0.01 | 0.04 |
| | (0.20) | (0.16) | (0.18) | (0.18) | (0.10) | (0.11) | (0.11) | (0.19) |
| FTIC | 0.22 | 0.20 | 0.21 | 0.20 | 0.42 | 0.33 | 0.32 | 0.16 |
| | (0.42) | (0.40) | (0.41) | (0.40) | (0.49) | (0.47) | (0.46) | (0.36) |
| N | 86,289 | 173,963 | 8,369 | 67,538 | 8,313 | 20,580 | 13,524 | 69,991 |

Table A.2
Results of Joint Test of Significance

| | Omnibus Test P-Value | | Average Percent Standardized Bias | |
|---|---|---|---|---|
| | Pre-Weighting | Post- Weighting | Pre- Weighting | Post- Weighting |
| | Scheme 1 | | | |
| FTIC 1-29% Credits Online Post-COVID | <0.001 | >.05 | 13.76% | 0.92% |
| FTIC 30-59% Credits Online Post-COVID | <0.001 | >.05 | 13.87% | 1.90% |
| FTIC 60-99% Credits Online Post-COVID | <0.001 | >.05 | 16.03% | 2.56% |
| FTIC 100% Credits Online Post-COVID | <0.001 | >.05 | 12.39% | 2.40% |
| Continuing 1-29% Credits Online Post-COVID | <0.001 | >.05 | 13.38% | 1.58% |
| Continuing 30-59% Credits Online Post-COVID | <0.001 | <.05 | 11.91% | 1.98% |
| Continuing 60-100% Credits Online Post-COVID | <0.001 | <0.001 | 16.73% | 3.06% |
| Continuing 100% Credits Online Post-COVID | <0.001 | <0.001 | 12.32% | 2.54% |
| | Scheme 2 | | | |
| Pre-COVID FTIC | <0.001 | >.05 | 9.03% | 0.71% |
| Post-COVID FTIC | <0.001 | >.05 | 13.09% | 2.05% |
| Pre-COVID Continuing | <0.001 | <0.001 | 10.03% | 0.89% |
| Post-COVID Continuing | <0.001 | <0.001 | 11.49% | 2.01% |
| | Scheme 3 | | | |
| Post-COVID FTIC Async Only | <0.001 | >.05 | 13.92% | 2.16% |
| Post-COVID FTIC Sync Only | <0.001 | >.05 | 11.26% | 0.76% |
| Post-COVID FTIC Both | <0.001 | >.05 | 14.56% | 2.20% |
| Post-COVID Continuing Async Only | <0.001 | <0.01 | 11.24% | 2.02% |
| Post-COVID Continuing Sync Only | <0.001 | >.05 | 8.04% | 0.51% |
| Post-COVID Continuing Both | <0.001 | <0.001 | 15.30% | 2.84% |

Table A.3
Total Marginal Effect of Annual Credits Attempted Online

| | | Annual GPA | | Credits Earned Annually | | Enrolled in the Fall | |
|---|---|---|---|---|---|---|---|
| Number | Predictor | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| 1 | Took Any Course Online | -0.003 | -0.021* | -0.340***+ | -0.024 | -0.043*** | -0.051*** |
| | | (0.007) | (0.017) | (0.032) | (0.069) | (0.003) | (0.009) |
| | N | 251,820 | | 259,995 | | 195,611 | |
| 2 | 1-29% credits online | | 0.001 | | -0.156 | | 0.006 |
| | | | (0.023) | | (0.122) | | (0.011) |
| | N | | 17,823 | | 18,621 | | 8,968 |
| | 30-59% credits online | | 0.013 | | -0.067 | | -0.023* |
| | | | (0.019) | | (0.093) | | (0.009) |
| | N | | 29,777 | | 30,820 | | 15,671 |
| | 60-99% credits online | | 0.058* | | -0.013 | | -0.045*** |
| | | | (0.023) | | (0.113) | | (0.011) |
| | | | 35,759 | | 36,680 | | 20,051 |
| | 100% credits online | | -0.065*** | | 0.074 | | -0.068*** |
| | | | (0.019) | | (0.062) | | (0.010) |
| | N | | 69,938 | | 73,359 | | 46,112 |
| 3 | Took Only Asynchronous | | -0.010 | | 0.96 | | -0.056*** |
| | | | (0.017) | | (0.070) | | (0.009) |
| | N | | 74,624 | | 77,468 | | 41,342 |
| | Took Only Synchronous | | -0.134*** | | -0.299*** | | -0.051*** |
| | | | (0.023) | | (0.071) | | (0.011) |
| | N | | 17,299 | | 18,669 | | 10,704 |
| | Took Both | | -0.010 | | -0.174 | | -0.048*** |
| | | | (0.023) | | (0.106) | | (0.011) |
| | N | | 51,391 | | 52,637 | | 33,549 |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. + denotes that the pre- and post-covid point estimates have a statistically significant difference. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for credits attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.

Table A.4
Total Marginal Effect of Annual Credits Attempted Online under Alternate Sample Constructions

| | | Annual GPA | | Credits Earned Annually | | Enrolled in the Fall | |
|---|---|---|---|---|---|---|---|
| Sensitivity Check | Predictor | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID | Pre-COVID | Post-COVID |
| Excluding Developmental Education | Took Any Course Online | -0.033*** | -0.024 | -0.323*** | 0.000 | -0.052*** | -0.061*** |
| | | (0.007) | (0.017) | (0.031) | (0.067) | (0.003) | (0.008) |
| | N | 248,672 | | 256,335 | | 192,446 | |
| | 1-29% credits online | | -0.001 | | -0.137 | | -0.003 |
| | | | (0.023) | | (0.122) | | (0.011) |
| | N | | 17,893 | | 18,625 | | 8,985 |
| | 30-59% credits online | | 0.014 | | -0.039 | | -0.032*** |
| | | | (0.019) | | (0.092) | | (0.009) |
| | N | | 29,774 | | 30,752 | | 15,662 |
| | 60-99% credits online | | 0.060** | | 0.023 | | -0.057*** |
| | | | (0.023) | | (0.112) | | (0.011) |
| | | | 35,461 | | 36,309 | | 19,809 |
| | 100% credits online | | -0.063*** | | 0.095 | | -0.079*** |
| | | | (0.019) | | (0.059) | | (0.009) |
| | N | | 69,725 | | 73,011 | | 45,897 |
| Excluding > 36 Credits | Took Any Course Online | 0.001 | -0.006 | -0.350***+ | -0.021 | -0.043*** | -0.056*** |
| | | (0.007) | (0.018) | (0.033) | (0.076) | (0.003) | (0.009) |
| | N | 240,794 | | 247,032 | | 186,322 | |
| | 1-29% credits online | | 0.005 | | -0.151 | | 0.004 |
| | | | (0.023) | | (0.122) | | (0.011) |
| | N | | 16,877 | | 17,451 | | 8,371 |
| | 30-59% credits online | | 0.022 | | -0.055 | | -0.026** |
| | | | (0.020) | | (0.096) | | (0.010) |
| | N | | 28,541 | | 29,338 | | 14,915 |
| | 60-99% credits online | | 0.063** | | -0.011 | | -0.049*** |
| | | | (0.024) | | (0.117) | | (0.011) |
| | | | 34,680 | | 35,374 | | 19,408 |
| | 100% credits online | | -0.051* | | 0.078 | | -0.078*** |
| | | | (0.020) | | (0.070) | | (0.011) |
| | N | | 64,376 | | 66,782 | | 42,253 |
| Including CTE Courses | Took Any Course Online | -0.024*** | -0.101*** | -0.705***+ | -1.134*** | -0.047*** | -0.097*** |
| | | (0.006) | (0.013) | (0.033) | (0.065) | (0.003) | (0.007) |
| | N | 289,228 | | 293,076 | | 218,195 | |
| | 1-29% credits online | | -0.064*** | | -0.809*** | | -0.007 |
| | | | (0.017) | | (0.096) | | (0.009) |
| | N | | 25,125 | | 25,513 | | 11,873 |
| | 30-59% credits online | | -0.060*** | | -0.936*** | | -0.037*** |
| | | | (0.015) | | (0.085) | | (0.008) |
| | N | | 37,095 | | 37,643 | | 18,894 |
| | 60-99% credits online | | -0.078*** | | -1.123*** | | -0.075*** |
| | | | (0.017) | | (0.098) | | (0.009) |
| | | | 47,353 | | 47,853 | | 25,864 |
| | 100% credits online | | -0.138*** | | -1.217*** | | -0.141*** |
| | | | (0.013) | | (0.059) | | (0.008) |
| | N | | 75,873 | | 77,099 | | 48,592 |

*Note*. * p<0.05, ** p<0.01, *** p<0.001. Pre-COVID includes AYs 2017/18 and 2018/19. After COVID includes AYs 2021/22, 2022/23, & 2023/24. Sample includes FTIC and continuing students. Estimates are the average marginal effect for credits attempted online before and since COVID, with all other variables set to their mean value. Standard errors clustered at the student-level.