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Increasing success in higher education: The relationships of online course taking with college completion and time-to-degree

Christian Fischer
University of Tübingen

Rachel Baker
University of California, Irvine

Qiujie Li
New York University

Gabe Avakian Orona
University of California, Irvine

Mark Warschauer
University of California, Irvine

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Increasing success in higher education: The relationships of online course taking with college completion and time-to-degree

Christian Fischer [a,*], Rachel Baker [b], Qiujie Li [c], Gabe Avakian Orona [b], Mark Warschauer [b]

[a] *University of Tübingen, Germany*

[b] *University of California, Irvine, United States of America*

[c] *New York University, United States of America*

* Corresponding author: christian.fischer@uni-tuebingen.de

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Abstract: Online courses provide flexible learning opportunities, but research suggests that students may learn less and persist at lower rates compared to face-to-face settings. However, few research studies have investigated more distal effects of online education. In this study we analyzed six years of institutional data for three cohorts of students in thirteen large majors (N=10,572) at a public research university to examine distal effects of students' online course participation. Using online course *offering* as an instrumental variable for online course *taking*, we find that online course taking of major-required courses leads to higher likelihood of successful four-year graduation and slightly accelerated time-to-degree. These results suggest that offering online course-taking opportunities may help students to more efficiently graduate college.

Keywords: Online learning, higher education, graduation rates, educational policy, educational effectiveness

Introduction

Success in postsecondary education is a key determinant for both individual career trajectories and for national prosperity and societal well-being (Moretti, 2004; National Academy of Sciences, National Academy of Engineering, & Institute of Medicine, 2007; Sianesi & Reenen, 2003). As high-paying, secure jobs increasingly require advanced skills to keep pace with technological developments, the bachelor's degree remains a primary avenue for low-income and historically marginalized groups to secure middle-class wages (Duncan & Murnane, 2014). However, recent statistics from the U.S. Department of Education (2017) indicate that, among first-time, full-time bachelor's degree-seeking students beginning at four-year institutions, only about 41% successfully graduate college within four years and 60% within six years.

Historically, research on student progression primarily focused on student-level characteristics and seldom addressed institutional inefficiencies that may delay or impede student graduation (Munro, 1981). More recent studies, however, have begun to closely examine how institutional policies and procedures affect graduation (e.g., Attewell, Heil, & Reisel, 2011; Scott-Clayton, 2015). For example, students' inability to enroll in required courses—due to capacity constraints on the part of the institution or scheduling constraints on the part of the student—can delay graduation (Gurantz, 2015; Pearson Foundation, 2011). Online course offerings may alleviate some of these supply- and demand-side constraints by allowing students to enroll in otherwise inaccessible courses which could potentially accelerate student time to graduation.

Online courses are an increasingly important part of students' college experience in the United States; even before the shift to emergency distance learning induced by the Covid-19 pandemic many students were enrolling in online classes. For instance, in 2016, more than 30 percent of all undergraduate students participated in online coursework (McFarland et al., 2018). Advocates of online education assert that online courses can provide greater and easier access to coursework for students while also serving as cost-effective forms of instruction for universities (Bartley & Golek, 2004; Waschull, 2001; Watson & Gemin, 2008). However, numerous studies indicate that near-term measures of student learning and performance (e.g., course completion, course grades, success in subsequent courses) are slightly lower in online settings as compared to traditional face-to-face environments (e.g., Bettinger, Fox, Loeb, & Taylor, 2017; Figlio, Rush, & Yin, 2013; Xu & Jaggars, 2013, 2014).

Much less work has examined how online courses affect more distal outcomes such as time-to-degree and graduation rates. This is an important to examine as departments may want to keep some of their online courses that were introduced during the Covid-19 pandemic. Online courses are a potentially effective method for reducing delays in completing course requirements. For students, the cost of potentially earning a lower grade in an online setting may be offset by the benefit of making more efficient progress toward graduation.

However, such effects may vary across student groups. Students with low-socioeconomic status (SES), first-generation college students, and students with relatively poorer academic preparation have longer average times-to-degree, controlling for institution type, than their more privileged counterparts (Gabriel, 2016; Ginder, Kelly-Reid, & Mann, 2017; Ishitani, 2006; Yates, 2010; Zarifa et al., 2018). As these students may also have greater demands on their time and thus require greater flexibility to accommodate their schedules (Grabowski, Rush, Ragen, Fayard, & Watkins-Lewis, 2016), online courses present an opportunity to manage external demands while progressing through degree programs (Stone, O'Shea, May, Delahunty, & Partington, 2016). However, students managing multiple external demands on their time might also lack access to campus resources and connections to supportive institutional figures, which could mean that taking online courses, which require greater self-regulation, could lead to negative consequences. Thus, it is crucial to understand the overall effect of taking classes online, as well as heterogeneous effects for traditionally underserved groups.

Background

Conceptual Framework

This study draws on Rovai's (2003) composite model of student persistence in online programs. The model posits that students' ability to persist in online courses relates to various student characteristics, student experiences, institutional policies and programs, and pedagogical styles. Combining Tinto's (1975, 1987, 1993) and Bean and Metzners' (1985) previous work examining persistence in higher education, Rovai categorizes these factors into two broad categories: those prior to admission to college and those after admission to college.

There are two broad domains of pre-admission characteristics: (1) student characteristics, including demographic background, academic performance and preparation, and (2) student skills, including facility with technology, information literacy, and time management. After admission, Rovai focuses on three sets of factors: (1) external factors, such as the students' financial situation, work hours, and personal and life circumstances; (2) institutional factors, such as the provision of support, course availability, and pedagogical features; and (3) individual factors, such as how well students integrate and identify with their studies, peers, and their institution.

These potential influences are not merely additive; student characteristics and skills interact with their environments. For example, students with high self-regulation will likely fare better in online classes than those with weaker self-regulatory skills (e.g., Baker et al., 2020; Broadbent & Poon, 2015; Li, Baker, & Warschauer, 2020). Similarly, external factors may affect students' decisions to take advantage of institutional support.

While Rovai's model focuses specifically on student progression within courses, we follow past work (e.g., Ortagus, 2018) that has extended the model to examine related outcomes (probability of graduation and time-to-degree). The model's focus on salient background student characteristics that are related to student success informs our covariate selection and subgroup analyses (i.e., first-generation college students, low-income students, students with weak academic preparation). Also, our study assumes that pre-admission characteristics influence the uptake of online course offerings (with the availability of online courses representing an after-admission institutional factor), as well as course and degree success.

Distal College Performance Indicators

Despite being understood as a four-year endeavor, across all public four-year institutions, only about 41% of first-time, full-time undergraduate students in the 2010 cohort graduated within four years, and about 60% graduated within six years (United States Department of Education, 2017). Graduation outcomes are correlated with student characteristics; low-income students, first-generation college students, and older (generally considered over age 21) students are much less likely to complete a bachelor's degree on time compared to their counterparts (Ewert, 2010; Zarifa et al., 2018).

Delayed graduation has economic consequences for society, for the institution, and for students (Hakkinen & Uusitalo, 2002; Jenkins & Rodriguez, 2013; Kurlaender. Jackson, Howell, Grodsky, 2014; Zarifa, Kim, Seward, & Walters, 2018). Longer time-to-degree has societal implications, such as a reduced supply of college-educated workers and greater burdens on state and federal loans. At the institutional level, prolonged time-to-degree may decrease institutional efficiency by increasing the amount of institutional resources devoted to an individual student and may result in educational changes such as larger class sizes (Jenkins & Rodriguez, 2013). And even for students who eventually graduate, there are economic consequences associated with prolonged enrollment. Taking longer to graduate may increase direct costs for students by increasing total tuition fees, inducing more borrowing which could mean occurring interest on earlier loans, increasing opportunity costs from foregone earnings, and potentially decreasing potential earnings in the labor market in the long run (Volkwein & Lorang, 1996; Witteveen & Attewell, 2021).

Factors Affecting Time-to-Degree

Institutional efforts to mitigate delayed graduation generally focus on social, financial, and academic support for students (Bettinger & Baker, 2014; Boyle, Kwon, Ross, & Simpson, 2010; Bryson & Hand, 2007; Hart, 2003; Rheinheimer, Grace-Odeleye, Francois, & Kusorgbor, 2010; Xu, Solanki, McPartlan, & Sato, 2018). However, such efforts seldomly address the institutional factors that often delay student trajectories. Research suggests that measures of how well institutions provide and structure resources for students—such as student-faculty ratios, program design, and expenditures on student services—are related to students' time-to-degree and eventual graduation (e.g., Bound, Lovenheim, & Turner, 2010; Chen, 2012; Goenner & Snaith, 2004; Shapiro, Dundar, Wakhungu, Yuan, Nathan, & Hwang, 2016; Kezar, 2006; Zarifa et al., 2018). Institutions have implemented a number of policies, structures, or programs to improve time-to-degree. For example, many schools offer summer courses, which may enable students to take coursework they could not complete during the regular academic year due to insufficient seating capacity or unmet academic course requirements (e.g., Adelman, 2006; Fischer et al., 2020; Smith & Byrd, 2015).

The institutional factors affecting time-to-degree are especially salient for first-year students, as the freshman year is a period of transition. Students in their first year are often not connected to institutional supports and the campus community, and many students lack the self-regulatory and time management skills necessary to thrive in unstructured academic environments (Bailey, Duffrin, Carels, & O'Brien, 2019; Bruffaerts et al., 2019; Koch & Gardner, 2014).

Recent work has sought to better understand how course offerings and curricular structures might affect student progress (Bailey, Jaggars, & Jenkins, 2015; Bhaskaran, Lu, &

Aali, 2017). For instance, constrained offerings may induce students to enroll in courses that do not count towards a degree because necessary courses are unavailable (Pearson Foundation, 2011). While the evidence on the effect of course scarcity on time-to-degree is mixed and context-dependent (e.g., Gurantz, 2015; Kramer, Holcomb, & Kelchen, 2018; Kurlaender, Jackson, Howell, & Grodksy, 2014; Yue & Fu, 2017), many students state that enrollment difficulties inhibit their ability to progress on time (Pearson Foundation, 2011), and there is a growing body of research examining the effects of overcrowding, enrollment intensity, and excess-credit hour policies on time-to-degree. One potential institutional response to alleviate pressures of course crowding is offering more online courses.

The Role and Effects of Online Learning in Higher Education

Online courses have become increasingly available in postsecondary education in the past ten years, even before the shift to emergency distance education due to the Covid-19 pandemic, and a significant number of students take classes online (Allen & Seaman, 2013; McFarland et al., 2018). For instance, in fall 2016, an estimated 5.2 million undergraduates (31% of all undergraduates) enrolled in at least one online course in the U.S. (McFarland et al., 2018). Several factors, at both the department and student levels, contribute to the growing availability and increasing enrollment rates of online classes.

There are multiple reasons why departments may decide to offer classes online. For instance, departments frequently offer introductory high-volume lecture courses in online settings to counteract resource constraints such as faculty teaching load and physical spaces (e.g., Geith & Vignare, 2008; Moloney & Oakley, 2010; Xu & Jaggars, 2011a; Xu & Xu, 2019). Departments may also offer online courses as a cost-saving measure to increase revenue from increased student enrollment (e.g., Herman & Banister, 2007). In addition, departments may offer online courses as opportunities for students to review and refresh critical knowledge to pass challenging subsequent gateway courses (e.g., Fischer et al., 2019; Zhou et al., 2019) or offer off-sequence or introductory courses online to allow students who did not pass the in-sequence course an opportunity to stay on-track for timely graduation (Watson & Gemin, 2008). Such courses are often offered in summer terms when many students at four-year residential colleges may not live on campus. This geographical flexibility of online classes benefits not only students, but also their instructors who are able to offer online courses independent of their residency (Alshare, Kwun, & Grandon, 2006; Hoffman, 2013). Some departments in traditional colleges even offer programs that are fully online to increase enrollment. For instance, Goodman, Melkers, and Pallais (2019) showed that the introduction of online M.Sc. in Computer Science programs leads to increased access to the program and subsequently higher number of awarded Computer Science degrees.

Online courses may provide opportunities for students to enroll in courses that they otherwise would not have been able to due to over-enrollment or departmental scheduling constraints (Gould, 2003; Lei & Gupta, 2010; Pearson Foundation, 2011). The flexible scheduling afforded by asynchronous online courses, and the geographic flexibility afforded by all online courses, can allow students to enroll in additional classes by meeting students' individual needs to avoid travel and by helping students avoid scheduling conflicts with jobs, internships, and other out-of-class commitments (Daymont, Blau, & Campbell, 2011; Hirschheim, 2005). Only classes can also provide opportunities for students to personalize their coursework to fit individual learning needs (Vanslambrouck, Zhu, Lombaerts, Philipsen, & Tondeur, 2018).

Although online courses are gaining popularity with departments and with students, they also pose challenges. Most importantly, success in online learning depends upon students having greater self-discipline and self-regulation skills than is required in face-to-face classes (Broadbent & Poon, 2015; Cho, Kim, & Choi, 2017; Cho, Woodward, Li, & Barlow, 2017; Firmin et al., 2014; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Parkes, Stein, & Reading, 2015; You, 2016). Although such self-regulation skills are also important in face-to-face environments, fixed course schedules and physically present teachers make these skills less important in traditional settings (Bork & Rucks-Ahidiana, 2013). Furthermore, students may feel more isolated from their peers in online classes than in face-to-face settings, as effective interpersonal interactions are more difficult to implement in online settings (Bernard et al., 2009; Jaggars & Xu, 2016; Kuo, Walker, Schroder, & Belland, 2014; Wong & Trinidad, 2004).

The effect of these challenges is reflected in research that indicates that students tend to perform worse in online courses as compared to face-to-face courses, particularly for students traditionally at-risk in college environments (Bettinger et al., 2017; Fischer, Xu, et al., 2020; Figlio et al., 2013; Hart, Friedmann, & Hill, 2018; Xu & Jaggars, 2011b, 2013, 2014; Yeboah & Smith, 2016). For example, Fischer, Xu, et al. (2020) found a penalty on course grade of about 0.1 of a grade (on a 4.0-0.0 A-F scale) for online course taking. Results of quasi-experimental studies suggest that the negative effects of online education extend beyond course grade to include course persistence (Xu & Jaggars, 2014), likelihood of repeating a course (Hart et al., 2018), and subsequent course grade in the subject sequence (Bettinger et al., 2017).

While several studies have examined the effect of online classes on proximal outcomes, relatively few studies have investigated whether online education affects students’ time-to-degree and other distal success metrics. Huntington-Klein, Cowan and Goldhaber (2016) found that participating in online courses lead to a smaller probability of successful graduation in community college settings. Other prior work found that students who enrolled in an online course early in their college path (first year and first term, respectively) graduated several months sooner than their counterparts (Ortagus, 2018; Sublett, 2019).

However, there are two important limitations of these extant studies: (1) most of these studies were situated in community college settings (e.g., Huntington-Klein et al., 2016; Sublett, 2019) which enroll different student populations and have considerably different structural constraints compared to traditional four-year colleges, and (2) while these studies have used relatively rigorous methods in an attempt to control for potential biases due to selection into online classes (e.g., propensity score matching and student- and instructor-fixed-effects), these methods cannot completely address such biases. This limited research highlights unanswered questions regarding the longer-term effects of online course taking, particularly in four-year colleges. For instance, whether online course taking reduces the likelihood of graduation or whether online course taking may increase the efficiency of graduation (i.e., fewer terms to degree). In this study we leverage plausibly exogenous variation in access to online classes to estimate the causal effect of taking online classes on student outcomes. While our study also cannot fully address all potential selection biases, we add a different credibly causal approach to the extant body of research and test the robustness of our results to a range of potential threats to validity.

Research Questions

Using a large institutional dataset, this study expands this nascent research base on the impacts of online course offerings on more distal success metrics. Specifically, we explore whether enrollment in online courses affected students' probability of graduating within four or six years and students' time-to-degree. This is of importance, particularly, for departments deciding whether to keep online courses in their teaching portfolio after the end of the Covid-19 pandemic. Thus, this study examined the following research questions (RQs):

RQ1: How does enrollment in major-required online courses affect students' probability of graduating within four or six years?

RQ2: How does enrollment in major-required online courses affect students' time-to-degree for students who graduate within six years?

RQ3: How does enrollment in major-required online courses affect students' four-year and six-year graduation rates and time-to-degree for student populations who are traditionally at-risk in college environments (i.e., first-generation college students, low-income students, students with weak academic preparation)?

Methodology

Study Setting

Institution. This study is situated at a large public research university in California. This university is comprehensive, offering more than 80 undergraduate degree programs in more than 15 schools. As of 2019, about 30,000 undergraduate students were enrolled in this institution. This college enrolls a diverse undergraduate student body with about 48% first-generation college students and 45% Pell grant recipients and is federally designated as a Hispanic-Serving Institution (HSI) and an Asian American and Native American Pacific Islander-Serving Institution (AANAPISI). While this university is moderately selective, with an acceptance rate of 25% for undergraduates, it has also been lauded as an "Upward-Mobility Machine" by the New York Times (Leonhardt, 2015), which is also mirrored in its mission to "catalyze the community and enhance lives."

The institution has substantially expanded its online course offerings, from 18 courses in 2009 to 93 courses in 2015 to 109 courses in 2017. Most online courses (78%) were offered in summer. During the time of this study, the university did not centrally organize online offerings; for the most part, instructors could decide whether to offer their courses online or in-person. Additionally, online course offerings were not centrally advertised; in the course enrollment window each term, students were able to view whether courses were offered in an online or face-to-face modality in the schedule of classes. Institutional knowledge and the historic schedules of classes indicate that all these online courses were offered asynchronously and were fully online without on-site, in-person interactions (that is, the classes were not offered in blended/hybrid learning formats). Notably, this structure of course offerings is like many residential four-year colleges in the United States and different from schools that offer fully online degree programs and actively market such programs to prospective students to, for instance, attract working adult populations.

Sample and Measures. Institutional data for this study come from the Registrar's Office, the Offices of Institutional Research, Admission, and Summer Session. This study examines six years of institutional data for three cohorts of newly matriculated degree-seeking students (those who entered in fall terms of 2009, 2010, and 2011) in thirteen of the largest majors at this university. While we initially planned to examine the 15 largest majors on campus (representing over 80% of students) the historic major requirements were unclear for two of these majors and when we contacted departmental administrators, we were unable to get sufficient information on the major-required courses for the 2009-2011 cohorts. Therefore, we excluded these two majors from our analyses.

Our analysis examining graduation rates includes students from the three cohorts who finished their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; sample 1). In addition, we restricted this sample to students who successfully graduated with a degree in one of these thirteen majors within six years to examine the effects of online class offerings on students' time-to-degree (sample 2).

Dependent variables in this study are dichotomous variables that indicate whether students graduated within four or six years (RQ1) and a continuous variable that represents students' time-to-degree in years (RQ2). The key independent variables, which we discuss in detail below, are measures of online course taking. Additionally, the analyses include a number of student-level covariates including dichotomous variables indicating students' gender, racial/ethnic background, low-income status, first-generation college student status, English language learner status, in-state residency, transfer student status, as well as continuous variables including students' admission score (i.e., combined SAT/ACT score), number of passed Advanced Placement (AP) exams, enrollment in summer terms, and enrollment in major-required courses in summer terms. Table 1 provides descriptive information and variable definitions of the student- and cohort-level variables in this study by sample.

[TABLE 1 ABOUT HERE]

Major-Required Online Courses. We focus on courses that were required for students to complete their majors. Information on major requirements were accessed from the publicly available general catalogue. In a few cases in which requirements were unclear, we contacted department representatives. For each of the analyzed majors, we collected information on the course requirements students need for successful major completion. Some requirements must be fulfilled by a specific course, while others can be fulfilled by taking one course from a list of options. In this analysis, we treated every course that would advance student progress towards school and departmental major requirements as a "major-required" course.

We examine all major-required courses offered and taken online in students' first four years. In our analytic sample, 8% of the students took at least one major-required course online in the first four years of their college career. On average, 3% of the major required courses were offered online (shown in Figure 1, details for each major in Appendix Table A1). Since these data are from a period when the institution was beginning to expand its offering of online courses, it is not surprising that only a small percentage of major-required courses were offered online and that students only took a small proportion of their major-required courses online. Nonetheless, Figure 1, panel A indicates that there are differences in major-required online course offering across majors within a cohort and across cohorts within a major, which is the variation that this study uses to examine the impact of course modality.

[FIGURE 1 ABOUT HERE]

In addition, we specifically examine major-required lower division courses offered and taken online *in students' first year*. Figure 1, panel B provides descriptive information for all lower division major-required courses offered and taken online across cohorts by major; details across cohorts by major are provided in Appendix Table A2. The decision to examine lower division courses is both empirically and theoretically motivated. First, because there is less flexibility in lower division requirements as compared to upper division requirements, we expect there to be a stronger relationship between courses offered online and courses taken online (a stronger first stage), even accounting for the fact that there is less identifying variation in this instrument than there is in the ever-offered instrument. Indeed, most major-required courses that students took online were lower division courses (about 63%). Also, focusing on major-required lower division courses also allows us to compare our results more directly with previous studies, which found that first-year online enrollment has particularly positive associations with longer-term academic success in community colleges settings (e.g., Ortagus, 2018). This focus is also theoretically motivated. The first year of college poses unique challenges to students that may play an especially large role in affecting academic success and retention (e.g., Koch & Gardner, 2014; Tinto, 1993); therefore, effects of taking classes online – both positive and negative – may be most pronounced in the first year.

Analytic Methods

Research questions 1 and 2. We examine the effects of enrollment in major-required online courses on students' four- and six-year graduation rates (RQ1) and time-to-degree (RQ2) with an instrumental variables approach. RQ1 is answered using the sample of students who finished in one of our thirteen included majors and RQ2 is answered using the subsample of students who finished in one of our thirteen majors and graduated within six years. We also use two versions of the independent variable: courses offered/taken online in the first four years of each starting cohort (model 1) and lower division courses offered/taken online in the first year of each starting cohort (model 2).

The goal of this study is to provide an unbiased estimation of the relationship between online course enrollment and student outcomes. Simple comparisons of outcomes between students who take a higher versus lower percentage of courses online may yield biased estimations; students who tend to take courses online might differ systematically from those who do not. For instance, students who live off campus may be more likely to enroll in online courses as compared to residential students. Students who live off campus may also be less likely to use academic resources available on campus, such as study spaces and one-on-one tutoring services, which may lead to comparatively lower achievement. Such unobserved student characteristics may be correlated with both the key explanatory variable (i.e., online course taking) and the outcome variables. Such correlations, when not properly accounted for, can lead to biased results.

Indeed, we found correlations between student observed characteristics and outcomes (columns 1 and 2 in Appendix Table A3) and student observed characteristics and the percentage of major-required courses that students took online (columns 3 and 4 in Appendix Table A3). These correlations suggest that students may systematically sort into taking courses online and that this sorting could bias estimations of the relationship between taking classes online and student outcomes. Although ordinary least squares (OLS) regression analyses control for observed student characteristics, there may be remaining unobserved characteristics that cannot be properly accounted for in traditional regression analyses. We present naïve OLS regressions predicting outcomes using measures of student online course taking and controlling for observed student characteristics in Appendix Table A4.

Thus, instead of OLS regression, we used an instrumental variable (IV) approach to address these unobserved selection issues to provide more plausibly causal estimates. IV techniques allow researchers to isolate exogenous variation in a potentially endogenous explanatory variable (e.g., taking an online course) and use only this exogenous portion to estimate the causal impact of the explanatory variable on a subsequent outcome (e.g., graduation rate and time-to-degree; Murnane & Willett, 2010).

Specifically, we instrument online course *taking* with online course *offering*. We argue that, after controlling for anything unique about a given major and anything unique about a given cohort of students, the offer of online courses to students at the major-by-cohort level is essentially exogenous. Conditional on the validity of this assumption (which we interrogate in depth below) instrumenting for online course taking with online course offering should provide unbiased estimates of the effect of online courses taking on student college completion and time-to-degree. Importantly, this estimation strategy only allows us to examine the relationship between online courses *that fulfill major requirements* and student outcomes. This focus relates to the specifics of our estimation strategy; we leverage variation in access to online classes across majors and cohorts. Figures 1 and 2 demonstrate sufficient variation in online course offerings across majors and cohorts, which mostly resulted from differences in individual faculty desires to offer classes online.

Reduced Form Estimates. Before we introduce our IV estimation strategy, we first present our reduced form models. That is, we predict our outcomes using our instrument while controlling for student-level covariates, major fixed effects, and cohort fixed effects:

$$Y_{imc} = \alpha + \varphi\ online\_offered_{mc} + \gamma\ X_i + \theta\ Y_{mc} + \zeta_m + \eta_c + \mu_{imc} \quad (1)$$

Y_{imc} is the outcome variable of student i in major m and cohort c. Three outcomes were examined: probability of earning a degree within 4 years / 6 years and time-to-degree measured in years.[1] $online\_offered_{mc}$ represents the plausibly exogenous offering of online classes for each cohort of each major. Depending on the model, this variable describes either (a) the percentage of all major-required courses that were offered online for a particular cohort or (b) the percentage of lower division major-required courses offered online in the first year of the particular cohort. X_i represents a vector of student covariates including students' racial/ethnic background, gender, first-generation student status, low-income status, English language learner status, California resident status, admission score, number of passed AP exams, number of enrolled summer terms, and number of major-required courses enrolled in summer. Y_{mc} represents a vector of covariates at the major-by-cohort level (e.g., cohort size). ζ_m and η_c are the major fixed effects and cohort fixed effects, which control for unobserved differences across majors and across cohorts. α *and* μ_{imc} represent the regression intercept and the not directly overserved additive error terms, respectively. We cluster the error at the major-by-cohort level, as this is the level of treatment assignment (Abadie et al, 2017) and the individual student level, as students who double majored or switched majors appear more than once in our data. We discuss the issue of multiple observations per student in more detail below.

While the reduced form estimates do not provide information about the effects of *taking* classes online on graduation outcomes (which the instrumental variables estimates do), they do provide the effects of *offering* classes online, conditional on the offering of online classes being plausibly exogenous at the major-by-cohort level. We believe that presenting these intent-to-treat estimates is important for two reasons: (1) estimates of the effects of offering, rather than taking, online classes, might be the more policy-relevant estimate for departmental administrators and (2) reduced form estimates are unbiased even in the face of weak instruments (Angrist & Krueger, 2001), and, as we discuss below, our instrument is weak in one of our analytic approaches.

Instrumental Variable Estimates. Our IV analysis follows a two-stage least squares format. The *first stage of the IV approach* predicts the endogenous regressor (i.e., percentage of courses taken online) using the plausibly exogenous predictor (i.e., percentage of major-required courses offered online) as well as the student-, major-, and cohort-level covariates. Thus, our first-stage equation is:

$$online\_taken_{imc} = \alpha + \delta\ online\_offered_{mc} + \gamma X_i + \theta Y_{mc} + \zeta_m + \eta_c + \mu_{imc} \quad (2)$$

where all terms are defined as above. $online\_taken_{imc}$ represent the percentage of major-required courses taken online for student *i* in major *m* and cohort *c*, respectively. Again, depending on the model, this variable describes either (a) the percentage of all major-required courses taken online in the first four years of enrollment or (b) the percentage of lower division major-required courses taken online in the first year of enrollment.

The *second stage of the IV approach* used the fitted values from the first stage to predict the outcomes. The main independent variable is now the predicted value of the percentage of classes a student would take online. Based on exogenous variation in online course availability, we assume that our originally endogenous predictor is now uncorrelated with any omitted variables.

$$Y_{imc} = \alpha + \beta\ \widehat{online\_taken}_{imc} + \gamma X_i + \theta Y_{mc} + \zeta_m + \eta_c + \mu_{imc} \quad (3)$$

Therefore, the coefficient β in our second-stage model will be an unbiased estimate of the impact of taking major-required courses online on the dependent variables of interest (i.e., graduation rate, time-to-degree).

Research question 3. We conducted heterogeneity analyses to examine the effects of taking online courses for student populations traditionally at-risk in college environments (i.e., first-generation college students, low-income students, and students with weaker academic preparation) as previous research has identified that nontraditional and historically marginalized students typically take longer to graduate (e.g., Zarifa et al., 2018) and that these same groups might perform less well in online classes (e.g., Figlio et al., 2013; Kaupp, 2012). Whereas the dichotomous first-generation college student status and low-income status variables allowed for straightforward differentiation between subpopulations, subgroups based on student admission scores were created by dividing students into high and low admission score groups using a median split procedure. Thus, we replicate the analytical methods for the first two RQs and include terms interacting online course taking and the subgroup indicators to compare students traditionally at-risk in college environments with their non-at-risk counterparts.

Assumptions of the IV approach. In order for the IV approach to be valid, five conditions must be met: the potential outcome of each individual must be independent of the treatment status of other individuals (the stable unit treatment value assumption, SUTVA), the instrument must have a relationship with the endogenous predictor (there must be a first stage), the instrument must be as good as randomly assigned, the instrument can only affect outcomes through the endogenous predictor (the exclusion restriction), and the effect of the instrument must be in the same direction for all subjects in the population of interest (there can be no defiers) (Cunningham, 2021). We address each of these assumptions below.

First, SUTVA states that the outcome for student i depends only on her treatment status and not the treatment status of any other student. That is, student i's time to graduation is affected by the number of online classes available to her, but not the number of online classes that are available to student $j \neq i$. While SUTVA is notoriously difficult to empirically assess (Cunningham, 2021), in this context it is a reasonable assumption. As all students in each cohort-major cell have the same treatment assignment, the offer of online courses to student $j \neq i$ should not affect student i's outcomes beyond classic peer effects, which we expect regardless of modality.

Second, differences in online course availability must affect students' online course taking (i.e., there must be a first stage). Conditional on individual student characteristics, major-by-cohort characteristics, major fixed effects, and cohort fixed effects, the percentage of major-required courses offered online must be correlated with the percentage of major-required courses taken online. We show this to be true in the first stage analyses presented in columns 1 and 2 in Tables 4 and 5.

Third, the instrument must be independent of potential outcomes and potential treatment assignments. In this case, this assumption would be violated if the offering of online classes was correlated with demographic changes or additional supports (e.g., increased advising or tutoring) at the major-by-cohort level. To interrogate this first threat, we examined the relationships between student and cohort characteristics and the proportion of classes offered online in each major for a particular cohort. We first identified the student and cohort characteristics that were significantly correlated with the outcome variables (e.g., low-income status, admission score, and English language learner status) and then investigated if these characteristics, aggregated at the major by cohort level, were systematically associated with measures of the major-required courses offered online (column 1 in Table 2) or the lower-division major-required courses offered online (column 2 in Table 2) in a given major and for a particular cohort using equation (4).

$$online\_offered_{mc} = \alpha + \omega X_{mc} + \kappa Y_{mc} + \zeta_m + \eta_c + \mu_{mc} \quad (4)$$

We find some evidence of significant relationships between these key student characteristics and online course offerings. Specifically, we find suggestive evidence that, controlling for major and cohort fixed effects, the number of classes offered online within a major-by-cohort cell is positively related to the percent of Black students, positively related to the percent of first-generation students, and positively related to the average admission score within that cell. When we examine the F-statistic of the joint significance of all student- and cohort-characteristics (measured at the major-by cohort-level), we find a significant relationship between student characteristics and major-required lower division courses offered online, but no significant relationship between student characteristics and all major-required courses offered online. Additional analyses indicated that the relationship between student characteristics and percent of lower-division major required courses offered online was driven mainly by a single major, Public Health. Columns 3 and 4 in Table 2 in present these analyses again without the Public Health major and indicate that there is no longer a significant relationship between student characteristics and the percent of lower division major-required classes offered online. A robustness check comparing the main results to results that excluded this major from the analysis indicated that results are very similar in magnitude and direction. The results are presented in the appendix (Table A5).

To interrogate the second threat to independence (online course offerings correlated with the provision of other services), we interviewed departmental administrators in three departments. All interviewees stated that the decision to offer courses online was made by individual instructors without departmental influence. These interviews indicated that instructors had two major incentives for offering courses online: (1) geographic flexibility when teaching courses and (2) small grants offered by the state system for putting courses online. Administrators stated that both incentives were available to instructors across all departments and that decisions to offer courses online were instructor-driven and idiosyncratic.

The administrators also confirmed that increases in online course offerings were not paired with additional student support or changes to departmental admissions requirements and were not correlated with cohort size. The interviews imply that there are no major-by-cohort-level variables that covary with online course offerings that could also affect student outcomes. Conditional on major- and cohort-fixed effects, we believe that the offering of online classes was essentially exogenous; decisions were not driven by administrators attempting to address student needs or affect student outcomes. This supports our IV modeling approach.

Fourth, the instrument must meet the exclusion restriction. That is, the instrument (percentage of major-required courses offered online) must not be directly related to the outcome variables (graduation rate, time-to-degree) *except* through its relationship with the endogenous predictor of interest (i.e., online courses taking). There is one main path by which the assumption that the only way the instrument (online course offerings) affects the outcomes is through the main predictor (online course taking) could be invalid: students could select into specific majors within a cohort based on online course offerings.

We investigate this possible violation empirically. Because access to advising, curricular structures, and peer composition varies across majors, if students select into majors based on availability of online classes, the instrument might affect outcomes via a path other than the endogenous regressor. As initial major selections are predominantly made before or during the college application process, and pre-enrolled students do not have reliable or systematic access to information about which classes are offered online, initial major choices are unlikely to be influenced by online course offerings. However, students can change majors after enrolling, and such subsequent choices may be affected by availability of online course offerings. We examine the extent of this threat through two separate robustness checks.

First, we interrogate if there is any evidence of students meaningfully sorting into majors within cohorts based on online classes offerings by examining the relationships between the percentage of students who switched into a given major and the percentage of all major-required courses offered online/major-required lower division courses offered online in that major. The results show that the relationships are small and not significant (Appendix Table A6).

Second, we examine the extent of the potential threat of students selecting a major within a cohort based on course offerings by replicating our main analyses on a subsample of students who never changed majors (i.e., students who started and ended with the same major). We include this analysis as a robustness check in the appendix (Table A7). Results are similar in direction compared with the main results, though not statistically significant, which is likely due to the reduced statistical power. We note that for these analyses, there is a relatively weak first stage which could lead to biased estimates from this instrumental variable approach (Staiger & Stock, 1994).

The final assumption of instrumental variables analyses is that increasing levels of, or opportunities to receive, treatment do not encourage or induce some individuals to get less treatment. This is commonly referred to as monotonicity and implies that there are no defiers – subjects who get the treatment when assigned to the control group and do not receive treatment when assigned to the treatment group (Angrist, Imbens, & Rubin, 1996; Imbens & Angrist, 1994). In this study, this translates to assuming that there is no one who would have taken more online courses if provided reduced online course offerings, but not taken more if provided increased online offerings. Importantly, this does not preclude the presence of always-takers (those who will get the treatment no matter their assignment status) and never-takers (those who will not get the treatment no matter their assignment status).

While we cannot fully interrogate the assumption that there are no defiers, we have some evidence that monotonicity holds in this context. The primary mode through which monotonicity could be violated is by students switching majors – a student could feel that because his major offers too few online classes, he needs to switch into a major with more online classes. As a specific example, a student may feel that four classes available online is sufficient but two is too few. In this case, the student may switch into a major with more classes available online – being assigned to fewer offered online classes induces him to take more. (The other direction of switching, a student switching out of a major that he feels offers too many online classes, is less likely in this context because the vast majority of classes were offered in-person and most classes that were offered online were also offered in person.) As we note above when discussing the exclusion restriction, we explicitly test for this behavior in our data and do not find evidence of major switching based on online course availability.[2]

Summer course taking. As we noted when describing the setting of this study, most online classes at our focal college were offered in the summer. Thus, the mechanisms through which offering classes online affects graduation outcomes could be summer course taking; online classes could induce students to enroll in summer terms when they otherwise would not have, which could increase graduation efficiency. While our analytic models include number of summer terms enrolled and number of major-required classes taken over the summer, which thus allows us to compare the graduation outcomes of students with similar summer course-taking patterns, we interrogate how large a role summer enrollment plays in explaining the relationship between online course taking and graduation outcomes in two ways.

First, we predict number of summer terms enrolled and number of major-required courses taken over the summer using our reduced form models (using number of major-required classes offered in year one/all four years as the predictor of interest and controlling for student-level covariates and major- and cohort-fixed effects). These models, presented in Appendix Table A8, indicate that the offering of online major-required classes induced students to enroll in fewer summer terms. Second, we re-estimate our main instrumental variable models, but do not include the number of summer terms enrolled and the number of major-required classes taken over the summer as control variables. Comparing the results of these models to the results from our main models allows us to examine to what extent overall summer enrollment mediates the relationship between online course taking and graduation outcomes. These models, presented in Appendix Table A9, produce findings very similar to our main results.

These findings indicate that overall summer enrollment is not the main mechanism by which online course taking affects graduation outcomes. This does not, however, indicate that summer course enrollment is not a mechanism explaining the relationship between online course offering and graduation outcomes, as online course offering could affect enrollment intensity or the timing of summer enrollment, but it does indicate that the relationship between online course offerings and graduation outcomes is not primarily driven by summer enrollment patterns.

Students enrolled in more than one major. Nearly 30% of students in our sample were officially enrolled in more than one of the thirteen majors during our period of observation. There are two, non-mutually exclusive, reasons for students to have multiple majors on record. Some students (28.8%) successfully fulfilled the requirements of more than one major and graduated as double or triple majors. Also, students could enroll sequentially in more than one major (major switchers). We found that 28.9% of students in our sample switched majors (not counting students who started as undeclared and thus had to “switch majors” to graduate). These students may pose a threat to the validity of our research design as our key instrument (number of classes offered online in the student’s major) is measured with noise for these students.

In our main models, we include one student-per-major observation. 29.4% of students have more than one observation since they enrolled in more than one of the thirteen majors. We prefer this specification as it reflects the fact that students are subject to the requirements of every major in which they are ever enrolled. In addition to accounting for multiple observations per student by clustering our standard errors at the student-level, we test the robustness of our results to this decision in three ways. First, as described above when discussing potential violations of the exclusion restriction in our instrumental variables approach, we limit our sample to students who start and end with the same major. The results of these analyses are similar in sign and magnitude to our main results, but they are not statistically significant. Second, we randomly select only one observation per student for all students who were ever enrolled in more than one major. The results of these analyses are very similar in magnitude, sign, and significance to our preferred models. Finally, we include all observations for all students but weight students' observations such that each student contributes equally to our estimates. These models also produce results that are similar in magnitude, sign, and significance to our preferred models. The results of these models are presented in the Appendix (Tables A10 and A11).

Missing data analysis. We use a listwise deletion approach as missingness was below 6.0% across all variables except for the admission score. Around 20% of students in our analytic sample did not have admission score data. Most of them (92.5%) were transfer students, who are not required to submit standardized test scores. We examined the sensitivity of our results to our decisions regarding missing data. First, we replicated our analyses on a sample that excludes all transfer students (Appendix Table A12). Second, we replicated our analyses using a dummy variable adjustment approach with the full sample of students who finished in one of the analyzed majors (Allison, 2002). All the results from the missing data analyses are consistent with the results of the main analysis in terms of the direction and strength of the coefficients (Appendix Table A13).

Results

Examining Associations with College Graduation Rates

We first examine if the offer of online classes is associated with changes in four-year and six-year graduation rates through our reduced form models. Estimates from these models are presented in Table 3. Each one percent increase in the number of major-required courses offered online is related to a 1.2% greater chance of a student successfully graduating within four years, $b = 1.233$, $SD = 0.42$, $p < 0.01$. Similarly, one percent increase in the proportion of first-year lower division major-required courses offered online is related to a 1.2% greater chance of successfully graduating within four years, $b = 1.232$, $SD = 0.39$, $p < 0.01$. We found no significant associations between the proportion of online courses offered and students' likelihood of graduating within six years for both all major-required courses and all first-year lower division major-required courses.

[TABLE 3 ABOUT HERE]

To examine whether online course *taking* impacts four-year and six-year graduation rates, we used an instrumental variables approach. We present the first- and second-stage estimates (Table 4). The first-stage analysis estimates the relationships between online course offering and online course taking and tests if the instrument is sufficiently strong to produce unbiased results. According to Staiger and Stock (1994), the estimation resulting from an instrumental variables approach could suffer from bias similar to the naive OLS regression when the partial correlation between the instruments and the endogenous variable is small. While there is not universal consensus on appropriate thresholds for F-statistics, recent literature suggests that in in this context (one endogenous regressor, one instrument, and a relatively conservative level of bias/distortion), the F-value should be greater than 16.38 (Stock & Yogo, 2005). The *F*-statistic on the instrument of all major-required courses offered online in the first four years was smaller than this threshold, $F(1,12) = 8.526$, $p < 0.01$. The F-statistic on the instrument of major-required lower division courses offered online in the first year was larger than the threshold, $F(1,12) = 74.823$, $p < 0.001$. Because of weak first-stage estimate for the first model (i.e., all major-required courses offered online in the first four years), we interpret results from these models with a degree of caution.

[TABLE 4 ABOUT HERE]

Table 4 shows the estimates of the relationships of online course enrollment on graduation rates using the IV approach. One percent increase in the proportion of major-required courses taken online is related to a 14.4% greater chance of successfully graduating within four years, $b = 14.375$, $SD = 7.78$, $p < 0.10$. Similarly, one percent increase in the proportion of first-year lower division major-required courses taken online is related to a 9.0% greater chance of successfully graduating within four years, $b = 8.955$, $SD = 2.66$, $p < 0.001$. There were no significant associations of the proportion of online courses taken and students' likelihood of graduating within six years both for all major-required courses and all first-year lower division major-required courses.

As is the case in all studies using instrumental variables, the effects we estimate are the local average treatment effects (LATE). This is the average treatment effect for the sub-population of compliers (here, those students who are induced to take more classes online because more are offered; Imbens & Angrist, 1994; Angirst, Imbens, & Rubin, 1996). These estimates do not necessarily apply to the always takers (those who would take online classes no matter what). The LATE can have weak external validity and the interpretation is dependent on the specific instrument we use. The effects we estimate might not hold if we were to, for example, randomly assign students to take online courses or if we were to leverage a different naturally occurring source of exogenous variation in online course taking. However, we believe that in this specific instance, the LATE is of great practical interest, as it answers a question that is informative to many departmental administrators.

Examining Associations with Time-to-Degree

We next examine effects on time-to-degree for students who graduated within six years. Table 3 presents estimates of the effect of *offering* major-required classes online on time-to-degree (our reduced form estimates). A one percent increase in the proportion of major-required lower division courses offered online is associated with a decrease of 1.3% of a year in student time to degree, corresponding to approximately 0.16 months. A one percent increase in the proportion of lower division courses offered online is associated with a decrease of 1.6% in student time to degree, corresponding to approximately 0.20 months.

We next tested whether *taking* online courses impacts students' time to degree by examining the subgroup of students who graduated college within six years, again using an instrumental variables approach. Table 5 shows the first- and second-stage estimates. The results from first-stage analysis were similar to those of the full sample. The F-statistic on the instrument of major-required lower division courses offered online in the first year was larger than the threshold, $F(1,12) = 76.212$, $p < 0.001$, but the F-statistic on the instrument of all major-required courses offered online in the first four years was slightly smaller than the established threshold, $F(1,12) = 8.009$, $p < 0.01$.

[TABLE 5 ABOUT HERE]

Notably, results from the second-stage analysis show that students' enrollment across all online courses in their first four years is not significantly associated with students' time-to-degree. However, students' enrollment in lower division online courses during their first year is significantly associated with shorter time-to-degree. A one percent increase in the proportion of lower division courses taken online is associated with a 12.0% decrease in time to degree, corresponding to approximately 1.4 months.

Heterogeneity Effects Regarding Student Graduation Rates and Time-to-Degree

To examine heterogeneous effects for student populations traditionally at-risk in college environments (i.e., first-generation college students, low-income students, students with weak academic preparation) on student graduation rates and time-to-degree, we included interaction terms in the instrumental variables analysis (Table 6).

[TABLE 6 ABOUT HERE]

Graduation rates. Heterogeneous impacts of online course taking were only evident in terms of student low-income status while there was no evidence for heterogeneous impacts in terms of first-generation status and academic preparation.

For non-first-generation college students, one percent increase in online course enrollment in major-required courses during the first four years is associated with a 14.0% greater chance of successfully graduating within four years and no significant effect for graduating within six years, which is not significantly different from the association for first-generation college students (columns 2 and 3 in Panel A Table 6). Similarly, for non-first-generation college students, one percent increase in online course enrollment in major-required lower division courses during the first year is associated with a 9.4% greater chance of successfully graduating within four years, which is not significantly different from the association for first-generation college students (column 2 in Table 6 Panel A). Again, no significant association was found for six-year graduation rates for non-first-generation college students or first-generation college students (column 3 in Table 6 Panel A)..

For non-low-income students, a one percent increase in online course enrollment in major-required courses during the first four years is associated with a 15.5% greater chance of successfully graduating within four years, which is not significantly different from the association for low-income students (column 2 in Table 6 Panel B). However, heterogeneous effects by income subgroups were found for major-required lower division courses taken online in the first year. For non-low-income students, a one percent increase in online course enrollment in major-required lower division courses during the first year is associated with a 11.6% greater chance of successfully graduating within four years. Notably, this increased chance of successfully graduating college within four years is lower for low-income students, $b = -5.176$, $SD = 2.20$, $p < 0.05$, when compared to non-low-income students (column 2 in Table 6 Panel B). For both non-low-income and low-income students, there were no significant effects regarding six-year graduation rates.

For students with strong academic preparation, similar results were found for online course enrollment in major-required lower division courses during the first year: enrolling in more major-required lower division courses during the first year is associated with similarly high chance of graduating in four years for students with strong academic preparation, $b = 9.823$, $SD = 3.30$, $p < 0.01$, and the association was not significantly different from that for students with weak academic preparation (column 2 in Table 6 Panel C). No effect was found for six-year graduation rates for either of the subgroups of academic preparation.

Time-to-degree. Heterogeneity analyses indicated that online course enrollments shortened students' time to college graduation for first-generation college students, low-income students, and students with weak academic preparation. However, this reduction in student time-to-degree is smaller (but greater than zero) for at-risk students compared to their non-at-risk counterparts.

For non-first-generation college students, one percent increase in online course enrollment in major-required lower division courses during the first year was associated with a decrease of 14.6% of a year in student time-to-degree, corresponding to approximately 1.8 months, $b = -14.623$, $SE = 4.19$, $p < 0.001$(column 5 in Table 6 Panel A). However, for first-generation college students, this time-to-degree decrease is approximately 0.7 months smaller when compared to non-first-generation college students, $b = 5.465$, $SE = 1.81$, $p < 0.01$ (column 5 in Table 6 Panel A).

For non-low-income students, one percent increase in online course enrollment in major-required lower division courses during the first year was significantly associated with a decrease of 18.5% of a year in student time-to-degree, which corresponds to approximately 2.2 months, $b = -18.489$, $SE = 4.85$, $p < 0.001$ (column 5 in Table 6 Panel B). However, for low-income students, this time-to-degree decrease is approximately 1.5 months smaller when compared to non-low-income students, $b = 12.205$, $SE = 4.19$, $p < 0.01$.

For students with strong academic preparation, one percent increase in online course enrollment in major-required lower division courses during the first year was associated with an approximate 2.5 months decrease in student time-to-degree, $b = -20.536$, $SE = 5.39$, $p < 0.001$ (column 5 in Table 6 Panel C). However, for students with weak academic preparation, this time-to-degree decrease is approximately 1.8 months smaller when compared to students with stronger academic preparation, $b = 15.016$, $SE = 3.94$, $p < 0.001$.

Discussion

This study applied Rovai's (2003) composite model of student persistence in online programs to understand the more distal outcomes of online course taking. In particular, this study attempted to isolate the effect of online course taking by carving out exogenous variation in online course taking using variation in departmental online course offerings. Extending the relevance of the conceptual framing to include longer-term effects is akin to previous research applying Rovai's model examining similar outcomes (e.g., Ortagus, 2018). Notably, we hope to inform educational administrators in their decision-making whether to retain some online course offerings in their course portfolios after the Covid-19 pandemic. Overall, this study extends the research base in three key ways:

First, most extant research has examined proximal college student outcomes such as course completion, course performance, and subsequent course success (e.g., Alpert, Couch, & Harmon, 2016; Bowen et al., 2014; Fischer et al., 2019; Fischer, Xu, et al., 2020). While these outcomes are important, especially the extent to which they measure student learning, they primarily serve as indicators of progress toward outcomes with important economic implications, such as eventual graduation and time-to-degree. This study directly examined such distal college success factors and thus contributes to a more nascent research base.

Second, most existing evidence of the effects of online course taking is situated at community colleges or for-profit universities (e.g., Bettinger et al., 2017; Kaupp, 2012; Xu & Jaggars, 2013, 2014). The student bodies and institutional contexts of community colleges and for-profit colleges are different from four-year institutions such that findings from these schools might not generalize to the four-year context. Thus, this study extends our understanding on distal effects of online course taking to residential four-year colleges.

Third, students select into online courses for several reasons, many of which are also related to the students' expected outcomes. Random assignment to online courses is difficult to implement. As the few studies that have done so have only assigned students to a single online course (Alpert et al., 2016; Bowen et al., 2014; Figlio et al., 2013; Joyce, Crockett, Jaeger, Altindag, & O'Connell, 2015), it is difficult to estimate causal effects of online course taking on students' more distal college outcomes. Failure to fully account for selection into online courses can bias estimates of the effects of online course taking. Indeed, we see evidence of this when comparing our baseline OLS estimates with our instrumental variables estimates (Table A1). When we do not leverage the exogenous variation in the number of online courses offered across majors over time, taking online courses appears to be, if anything, associated with a lower probability of graduating within four years and a longer time-to-degree. We find the opposite in our estimates in which we instrument online course taking with online course offerings.

Conclusion and Implications

The most important finding of this study is the following: Online course taking is associated with more efficient college graduation; students who are given the opportunity to take classes online graduate more quickly than those who are not. We also found that online course taking is associated with a higher likelihood of successfully graduating college within four years. It is important to note that the magnitudes of the coefficients need to be interpreted with caution for two reasons. First, since the distribution proportion of major required courses taken online is right-skewed, it is not clear that the estimated effects should be thought to extrapolate beyond the small range of observed values. Second, since we are not able to identify compilers in the sample, we do not know the distribution of percent of major required courses taken online, four-year graduation rates, and time to degree for this group and are not able to interpret how large the coefficients are relative to baseline rates. Despite the limitations in the interpretation of the magnitudes of the coefficients, our results are robust to a number of model specifications and analytic strategies in terms of the direction and significance level of the coefficients. The consistency of our results is important, as each of our models presents unique limitations.

These are promising findings. Despite somewhat lower student performance in online courses compared to their corresponding face-to-face courses (Bettinger et al., 2017; Figlio et al., 2013; Fischer, Xu, et al., 2020; Kaupp, 2012; Xu & Jaggars, 2013, 2014), our study finds that online courses may provide distal benefits for students to graduate college efficiently. Notably, our results are consistent with the limited existing quasi-experimental research examining online course-taking patterns and time-to-degree using nationally representative data sets (Shea & Bidjerano, 2014; Ortagus, 2018; Sublett, 2019). This is in contrast to research on distal impacts of online courses situated at single state-wide community college systems which has found online course taking to be associated with lower college persistence, transfer rates, and graduation rates (Huntington-Klein et al., 2017; Jaggars & Xu, 2010; Shea & Bidjerano, 2018; Xu & Jaggars, 2011a). This highlights the need for research to examine the effectiveness of online courses in various contexts.

To put the findings from this study in context, in the last decade there have been several institutional strategies put forth to reduce undergraduate time-to-degree, such as limiting credit requirements for programs, publishing term-by-term road maps for undergraduates, and guaranteeing the transfer of general education curriculum (Complete College America, 2011). These represent a mix of informational (e.g., degree maps) and programmatic (e.g., credit requirements) solutions. This study identifies another programmatic strategy for decreasing time-to-degree: offering more online classes.

Academic research on the effectiveness of such strategies is scant. While there is a fairly large literature examining individual characteristics or attributes associated with longer degree completion times (e.g., Behr and Theune (2016) identify that off-campus work extends time-to-degree approximately one term, and Yue and Fu (2017) find that double-majoring, entering college undeclared, and switching majors is associated with extended time to degree) there is less work that looks at the effects of policies and programs on time-to-degree.

A few recent studies, however, do show that institutional policies can significantly affect time to degree. For example, Baker et al. (2021) find that associate degrees specifically structured to support transfer to four-year schools (thus reducing the complexity of making course choices) reduces time to degree at the four-year college by 0.03-0.16 semesters. Sadoff and Brownback (2020) find that an intervention to increase enrollment in summer courses for students in community college leads to a 31% increase in graduation within one year and no increase within two years. Similar to the results in our study, they conclude that the effect is on degree acceleration and not overall attainment. Most akin to our study is Sublett's (2019) analysis of community college students time-to-degree. In this study, time-to-degree for both an associate degree and bachelor's degree was reduced by about 3 months by taking a distance education course in the first year. This reduction is similar to this study regarding increases in online course enrollment in major-required lower division courses during the first year.

Efforts to improve existing online courses by, for instance, providing students with more opportunities to improve their self-regulation skills (e.g., Broadbent & Poon, 2015; Cho et al., 2017; You, 2016), are laudable. However, departments should recognize that online courses may bring distal benefits even if student performance lags slightly in them. The added flexibility to course-taking for both the student (e.g., to accommodate their schedules) and the institution (e.g., to address capacity constraints) increases overall access of opportunities for students to earn course credits, which, in turn, may help with students' degree efficiency. For instance, students may be able to squeeze in that one additional course they are missing to graduate in a given semester instead of having to potentially enroll for another term (with the added tuition fees).

Students who are generally considered at-risk in college environments also show a small advantage from enrollment in online courses to graduate more efficiently. Compared to their non-at-risk counterparts, first-generation college students, low-income students, and students with weaker academic preparation have considerably smaller, but still positive, benefits of online course enrollments on distal college success factors. Detecting these reduced benefits of online course enrollment are in line with prior research suggesting that online course environments pose additional challenges to at-risk students (e.g., Figlio et al., 2013; Kaupp, 2012; Xu & Jaggars, 2013, 2014). Nonetheless, this study indicates that online courses can potentially benefit students on distal college success factors without adversary effects for students who are traditionally at-risk in college environments.

Overall, our study intends to inform departments at residential universities that traditionally offer just a few or no online courses, as the effects presented in this study were found for departments offering on average about 3% of online courses with an average of about 8% of students ever enrolling in an online class. Thus, even departments that did not typically include online courses in their teaching portfolio prior to the Covid-19 pandemic may consider retaining or increasing some of their online courses to increase the likelihood of students successfully completing course requirements and graduating.

Limitations

While online courses are increasingly important for colleges, many four-year schools, and particularly selective four-year schools, typically do not offer a significant proportion of their courses online. Since online course offerings have grown significantly over the past decade, it may be important to verify the generalizability of our results with more recent cohorts as the structure and quality of online courses has improved significantly in the past decade and Covid-19 may change how administrators and universities value online instruction (Sin & Muthu, 2015; Xu & Xu, 2019). We would not be surprised to see the benefits of online course enrollments replicated in settings that offer even higher quality online courses.

This study examines the effects of taking online courses to fulfill major requirements but does not examine the effects of online courses taken for other reasons, such as to fulfill general education requirements. If course enrollment decisions vary across contexts (for example, if students are more willing to opt into online courses for general education requirements than for major requirements or online courses were perceived to be of poor/high quality at certain departments), we may also find that effects of offering online courses differ across contexts.

As with any instruments that do not utilize random assignment, it is difficult to fully interrogate the exclusion restriction for our instrument. We cannot fully rule out the possibility that the instrument could have an effect on the outcomes we examine in any way other than through the number of online courses taken. Also, our instrument is weak for the smaller sample of students who started and ended with the same major and somewhat weak for when examining online courses offered/taken across the first four years of a student's enrollment. We believe there are two important contextual explanations for this. First, related to the point above, because online course offerings were relatively sparse at this school in this time period, our instrument lacks the type of variation one would like to see. This may limit our ability to identify positive effects. This is likely related to our range of years included in the data (i.e., 2009, 2010, 2011 cohorts) which were situated at the beginning of the expansion of online course offerings at this institution. Future research that uses later starting cohorts (e.g., 2017, 2018, 2019 cohorts) may find larger variation in online course offerings and yield more conclusive results. Second, our instrument (major-required classes offered online) includes any classes that can be used to fulfill major requirements, whether or not they are required. For example, if the requirements for major X include “take Course A and one course from the list: Course B, Course C, Course, D, and Course E” we consider all five courses to be required for the major. As lower division courses tend to be more prescribed and less flexible than upper division courses, this implies that the instrument will be stronger for lower division (first year) courses than upper division courses.

Finally, while course requirements represent the general rules for earning a degree in a certain major, they are, in certain cases, somewhat flexible. Thus, our analyses represent a noisy estimate of the effects of taking online courses on time-to-degree. And if certain students—those who are especially savvy or those who face especially strong struggles in completing coursework—petition to use specific online courses to fulfill their major requirements, our results could be biased upwards or downwards. While this is a legitimate concern, at large state schools, such as the one we examined, there is typically relatively little leeway for making bespoke curricular adjustments based on student petitioning. That said, our analysis is based on a single institution, which may limit its potential generalizability across the country but encourages replication analyses at other institutions.

Promising Directions for Future Research

The encouraging results from this study motivate several directions for future research. First, although we show in this study that online course taking, especially early in one's academic trajectory, can shorten time-to-degree, distal efficiency must be considered in tandem with the proximal penalties to academic performance attributed to online courses when compared to traditional face-to-face courses (e.g., Bettinger et al., 2017; Figlio et al., 2013; Fischer, Xu, et al., 2020; Xu & Jaggars, 2013, 2014). Therefore, an analysis to compare tuition savings and lifetime earnings for those who graduate earlier due to online course taking against individuals who learn, and possibly pay, more for taking longer and enrolling in face-to-face courses could shed some light on the overall costs and benefits. Second, with the number of online courses growing rapidly, even aside from the sudden shift to emergency distance education induced through the Covid-19 pandemic, future studies can confirm whether the trends noted here seem stable over time. Third, this study examines fully online courses that are mostly asynchronous. Given the existence of blended learning/hybrid course formats in higher education (Vo et al., 2017), we encourage researchers to also examine impacts of hybrid course enrollments with distal college outcome measures. Fourth, with the increased availability of large-scale institutional data (Fischer, Pardos, et al., 2020), continued studies of this type at other institutions of various types can confirm whether the benefits in aiding graduation rates and time-to-degree noted in this study are similarly found across different college settings. Finally, we examined the influence of online courses in programs that offer both face-to-face and online courses. Following the growing popularity of fully online programs (e.g., Goodman et al., 2019), future research is also encouraged to examine the potential and success of fully online programs that are situated at traditional residential universities.

Endnotes

1. We also examine the outcome of time-to-degree measured by terms. The results are presented in the appendix (Table A14) and are similar to the results of the main analysis using time-to-degree measured by years.

2. As shown in Figures 1 and 2, there are some cases within a cohort or within a major in which percentage of classes taken online decreases as percentage offered online increases. We do not take this as definitive evidence of a violation of monotonicity. Rather, we consider this relaxing the deterministic monotonicity assumption, akin to Small and colleagues (2017) concept of stochastic monotonicity. This assumption states that after conditioning "on all the measured and unmeasured confounders of the relationship between the treatment and outcome, then within each stratum, the probability of taking the treatment for subjects given the encouraging level of the IV is at least a high as for subjects given the non-encouraging level" (p. 563). Here, this would imply that when comparing the effect of the instrument (percentage offered online) on the endogenous predictor (percentage taken online), we will observe monotonicity when controlling for important confounding characteristics of the instrument.

There are a few factors related to stochastic monotonicity that are important in this context. In each major-by-cohort cell, a different set of courses can be offered online, and these courses can differ on dimensions such as perceived difficulty, perceived interest, which requirements they fulfill, schedule, etc. As students choose courses based on all of these dimensions, the distribution of these characteristics in online classes will affect the strength of the instrument (and will mean that the instrument is differentially strong across cohorts within a major and across majors within a cohort). More online classes offered might not always translate into more online classes taken if classes that are less appealing in other dimensions are more likely to be offered online in certain years. This implies that our instrument will be slightly noisy, and that a percentage increase in offered will be met with the same percentage increase in taken is not expected.

References

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college*. US Department of Education.

Allen, I. E., & Seaman, J. (2013). *Changing course: Ten years of tracking online education in the United States*. Newburyport, MA: Sloan Consortium.

Allison, P. D. (2002). *Quantitative Applications in the Social Sciences: Missing data.* Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781412985079

Alpert, W. T., Couch, K. A., & Harmon, O. R. (2016). A randomized assessment of online learning. *American Economic Review*, *106*(5), 378-82.

Alshare, K., Kwun, O., & Grandon, E. E. (2006). Determinants of instructors' intentions to teach online courses: A cross-cultural perspective. *Journal of Computer Information Systems*, 46(3), 87-95.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. Journal of the American statistical Association, 91(434), 444-455.

Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives, 15*(4), 69-85.

Attewell, P., Heil, S., & Reisel, L. (2011). Competing explanations of undergraduate noncompletion. *American Educational Research Journal*, *48*(3), 536-559.

Bailey, E. J., Duffrin, M., Carels, R., & O’Brien, K. (2019). The ‘Freshman 15’: Exploring weight issues, eating patterns, psychological, mental health, stress, and weight loss prevention programs among college students at East Carolina University. *J Community Med Public Health Care*, *6*, 044.

Bailey, T. R., Jaggars, S. S., & Jenkins, D. (2015). *Redesigning America's community colleges*. Harvard University Press.

Baker, R., Xu, D., Park, J., Yu, R., Li, Q., Cung, B., ... & Smyth, P. (2020). The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: Opening the black box of learning processes. *International Journal of Educational Technology in Higher Education*, *17*, 1-24.

Bartley, S. J., & Golek, J. H. (2004). Evaluating the cost effectiveness of online and face-to-face instruction. *Journal of Educational Technology & Society*, *7*(4), 167–175.

Bean, J., & Metzner, B. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research, 55,* 485–650.

Behr, A., & Theune, K. (2016). The causal effect of off-campus work on time to degree. *Education Economics*, *24*(2), 189-209.

Bernard, R. M., Abrami, P. C., Borokhovski, E., Wade, C. A., Tamim, R. M., Surkes, M. A., & Bethel, E. C. (2009). A meta-analysis of three types of interaction treatments in distance education. *Review of Educational Research*, *79*(3), 1243–1289.

Bettinger, E. P., & Baker, R. B. (2014). The effects of student coaching: An evaluation of a randomized experiment in student advising. *Educational Evaluation and Policy Analysis*, *36*(1), 3-19.

Bettinger, E. P., Fox, L., Loeb, S., & Taylor, E. S. (2017). Virtual classrooms: How online college courses affect student success. *American Economic Review*, *107*(9), 2855–2875.

Bhaskaran, S. S., Lu, K., & Aali, M. A. (2017). Student performance and time-to-degree analysis by the study of course-taking patterns using J48 decision tree algorithm. *International Journal of Modelling in Operations Management*, *6*(3), 194-213.

Bork, R. H., & Rucks-Ahidiana, Z. (2013). *Role ambiguity in online courses: An analysis of student and instructor expectations* (CCRC Working Paper No. 64). New York, NY: Community College Research Center, Teachers College, Columbia University.

Bound, J., Lovenheim, M., & Turner, S. (2012). Increasing time to baccalaureate degree in the United States. *Education Finance and Policy, 7*(4), 375-424.

Bowen, W. G., Chingos, M. M., Lack, K. A., & Nygren, T. I. (2014). Interactive learning online at public universities: Evidence from a six-campus randomized trial. *Journal of Policy Analysis and Management*, *33*(1), 94-111.

Boyle, F., Kwon, J., Ross, C., & Simpson, O. (2010). Student–student mentoring for retention and engagement in distance education. *Open Learning: The Journal of Open, Distance and e-Learning*, *25*(2), 115-130.

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

Brownback, A., & Sadoff, S. (2020). College Summer School: educational benefits and enrollment preferences. Available at SSRN 3622279.

Bruffaerts, R., Mortier, P., Auerbach, R. P., Alonso, J., Hermosillo De la Torre, A. E., Cuijpers, P., ... & Stein, D. J. (2019). Lifetime and 12-month treatment for mental disorders and suicidal thoughts and behaviors among first year college students. *International Journal of Methods in Psychiatric Research*, *28*(2), e1764.

Bryson, C., & Hand, L. (2007). Promoting student engagement. Paper presented at the *International Society for Scholarship of Teaching and Learning Conference,* Sydney, Australia.

California Community Colleges Chancellor's Office. (2017). *Distance education report*. Retrieved from California Community Colleges website: http://californiacommunitycolleges.cccco.edu/Portals/0/Reports/2017-DE-Report-Final-ADA.pdf

Chen, R. (2012). Institutional characteristics and college student dropout risks: A multilevel event history analysis. *Research in Higher Education*, *53*(5), 487-505.

Cho, M. H., & Kim, B. J. (2013). Students' self-regulation for interaction with others in online learning environments. *The Internet and Higher Education*, *17*, 69-75.

Cho, M.-H., Kim, Y., & Choi, D. (2017). The effect of self-regulated learning on college students' perceptions of community of inquiry and affective outcomes in online learning. *The Internet and Higher Education*, *34*, 10–17.

Cho, B. Y., Woodward, L., Li, D., & Barlow, W. (2017). Examining adolescents' strategic processing during online reading with a question-generating task. *American Educational Research Journal*, *54*(4), 691-724.

Cunningham, S. (2021). *Causal inference: The mixtape*. New Haven, CT: Yale University Press.

Daymont, T., Blau, G., & Campbell, D. (2011). Deciding between traditional and online formats: Exploring the role of learning advantages, flexibility, and compensatory adaptation. *Journal of Behavioral and Applied Management*, *12*(2), 156–175.

Duncan, G. J., & Murnane, R. J. (2014). *Restoring opportunity: The crisis of inequality and the challenge for American education*. Cambridge, MA: Harvard Education Press.

Ewert, S. (2010). Male and female pathways through four-year colleges: Disruption and sex stratification in higher education. *American Educational Research Journal, 47*(4), 744-773.

Figlio, D., Rush, M., & Yin, L. (2013). Is it live or is it internet? Experimental estimates of the effects of online instruction on student learning. *Journal of Labor Economics*, *31*(4), 763–784. https://doi.org/10.3386/w16089

Firmin, R., Schiorring, E., Whitmer, J., Willett, T., Collins, E. D., & Sujitparapitaya, S. (2014). Case study: Using MOOCs for conventional college coursework. *Distance Education*, *35*(2), 178–201. https://doi.org/10.1080/01587919.2014.917707

Fischer, C., Pardos, Z., Baker, R. S., Williams., J. J., Smyth, P., Yu, R., Slater, S., Baker, R., & Warschauer, M. (2020). Mining big data in education: Affordances and challenges. *Review of Research in Education, 44*(1), 130-160. https://doi.org/10.3102/0091732X20903304

Fischer, C., Xu, D., Rodriguez, F., Denaro, K., & Warschauer, M. (2020). Effects of course modality in summer session: Enrollment patterns and student performance in face-to-face and online classes. *The Internet and Higher Education, 45*, 1-9. https://doi.org/10.1016/j.iheduc.2019.100710

Fischer, C., Zhou, N., Rodriguez, F., Warschauer, M., & King, S. (2019). Improving college student success in organic chemistry: Impact of an online preparatory course. *Journal of Chemical Education, 96*(5), 857-864. http://dx.doi.org/10.1021/acs.jchemed.8b01008

Geith, C., & Vignare, K. (2008). Access to education with online learning and open educational resources: Can they close the gap? *Journal of Asynchronous Learning Networks*, 12(1), 105-126.

Ginder, S. A., Kelly-Reid, J. E., & Mann, F. B. (2017). *Graduation Rates for Selected Cohorts, 2008-13; Outcome Measures for Cohort Year 2008; Student Financial Aid, Academic Year 2015-16; and Admissions in Postsecondary Institutions, Fall 2016: First Look* (Provisional Data). NCES 2017-150rev. National Center for Education Statistics.

Goodman, J., Melkers, J., & Pallais, A. (2019). Can online delivery increase access to education? *Journal of Labor Economics*, *37(*1), 1-34.

Goenner, C. F., & Snaith, S. M. (2004). Predicting graduation rates: An analysis of student and institutional factors at doctoral universities. *Journal of College Student Retention: Research, Theory & Practice*, *5*(4), 409-420.

Gould, T. (2003). Hybrid classes: Maximizing institutional resources and student learning. In *Proceedings of the 2003 ASCUE Conference*. Myrtle Beach, SC.

Grabowski, C., Rush, M., Ragen, K., Fayard, V., & Watkins-Lewis, K. (2016). Today's non-traditional student: Challenges to academic success and degree completion. *Inquiries Journal, 8*(03).

Gurantz, O. (2015). Who loses out? Registration order, course availability, and student behaviors in community college. *The Journal of Higher Education*, *86*(4), 524-563.

Hakkinen, I., & Uusitalo, R. (2003). *The effect of student aid reform on graduation times, A duration analysis*. Uppsala University, Department of Economics, Working Paper Series. Retrieved from: https://ideas .repec.org/p/hhs/uunewp/2003_008.html.

Hart, N. K. (2003). Best practices in providing nontraditional students with both academic and financial support. *New Directions for Higher Education*, *121*, 99-106.

Hart, C. M., Friedmann, E., & Hill, M. (2018). Online course-taking and student outcomes in California community colleges. *Education Finance and Policy*, *13*(1), 42-71.

Herman, T., & Banister, S. (2007). Face-to-face versus online coursework: A comparison of learning outcomes and costs. *Contemporary Issues in Technology and Teacher Education*, *7*(4), 318-326.

Hirschheim, R. (2005). The internet-based education bandwagon: Look before you leap. *Communications of the ACM*, *48*(7), 97–101.

Hoffman, M. S. (2013). *An examination of motivating factors on faculty participation in online higher education* (Doctoral dissertation, Northeastern University).

Huntington-Klein, N., Cowan, J., & Goldhaber, D. (2017). Selection into Online Community College Courses and Their Effects on Persistence. *Research in Higher Education*, *58*, 244–269.

Imbens, G. W., J. D. Angrist 1994: Identification and Estimation of Local Average Treatment Effects, Econometrica, 62 (2), 467-475.

Ishitani, T. T. (2006). Studying attrition and degree completion behavior among first-generation college students in the United States. *The Journal of Higher Education*, *77*(5), 861–885.

Jaggars, S. S., & Xu, D. (2010). *Online learning in the Virginia community college system* (CCRC Working Paper). New York, NY: Columbia University, Teachers College, Community College Research Center.

Jaggars, S. S. (2011). *Online learning: Does it help low-income and underprepared students?* CCRC Brief. Number 52. Community College Research Center, Columbia University.

Jaggars, S. S. (2014). Choosing between online and face-to-face courses: Community college student voices. *American Journal of Distance Education*, *28*(1), 27-38.

Jaggars, S. S., & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education*, *95*, 270–284.

Jenkins, D., & Rodriguez, O. (2013). Access and success with less: Improving productivity in broad-access postsecondary institutions. *The Future of Children*, 187-209.

Johnson, N. (2011). Three Policies to Reduce Time to Degree. Complete College America.

Joyce, T., Crockett, S., Jaeger, D. A., Altindag, O., & O'Connell, S. D. (2015). Does classroom time matter? *Economics of Education Review*, *46*, 64–77.

Kaupp, R. (2012). Online penalty: The impact of online instruction on the Latino-White achievement gap. *Journal of Applied Research in the Community College*, *19*(2), 3–11.

Kezar, A. J. (2006). The impact of institutional size on student engagement. *NASPA Journal*, *43*(1), 87-114.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education*, *104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Koch, A., & Gardner, J. N. (2014). A history of the first-year experience in the United States during the twentieth and twenty-first centuries: Past practices, current approaches, and future directions. *The Saudi Journal of Higher Education*, *11*, 11-44.

Kramer, D. A., Holcomb, M. R., & Kelchen, R. (2018). The costs and consequences of excess credit hours policies. *Educational Evaluation and Policy Analysis*, *40*(1), 3-28.

Kuo, Y.-C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education*, *20*, 35–50.

Kurlaender, M., Jackson, J., Howell, J. S., & Grodsky, E. (2014). College course scarcity and time to degree. *Economics of Education Review*, *41*, 24-39.

Lee, D. L., McCrary, J., Moreira, M. J., & Porter, J. (2020). Valid t-ratio Inference for IV. arXiv preprint arXiv:2010.05058.

Lei, S. A., & Gupta, R. K. (2010). College distance education courses: Evaluating benefits and costs from institutional, faculty and students' perspectives. *Education*, *130*(4), 616–632.

Leonhardt, D. (2015). California's Upward-Mobility Machine. Retrieved from https://www.nytimes.com/2015/09/17/upshot/californias-university-system-an-upward-mobility-machine.html

Li, Q., Baker, R., & Warschauer, M. (2020). Using clickstream data to measure, understand, and support self-regulated learning in online courses. *The Internet and Higher Education, 45*. https://doi.org/10.1016/j.iheduc.2020.100727

McFarland, J., Hussar, B., de Brey, C., Snyder, T., Wang, X., Wilkinson-Flicker, S., Gebrekristos, S., Zhang, J., Rathbun, A., Barmer, A., Bullock Mann, F., & Hinz, S. (2017). *The condition of education 2017* (NCES 2017-144). US Department of Education. Washington, DC: National Center for Education Statistics.

Moloney, J. F., & Oakley, B. (2010). Scaling online education: Increasing access to higher education. *Journal of Asynchronous Learning Networks, 14*(1), 55-70.

Moretti, E. (2004). Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics, 121*(1–2), 175–212.

Munro, B. H. (1981). Dropouts from higher education: Path analysis of a national sample. *American Educational Research Journal, 18*(2), 133-141.

Murnane, R. J., & Willett, J. B. (2010). *Methods matter: Improving causal inference in educational and social science research*. Oxford University Press.

National Academy of Sciences, National Academy of Engineering, & Institute of Medicine. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future*. Washington, DC: National Academies Press.

Ortagus, J. C. (2018). National evidence of the impact of first-year online enrollment on postsecondary students' long-term academic outcomes. *Research in Higher Education, 59*(8), 1035-1058.

Parkes, M., Stein, S., & Reading, C. (2015). Student preparedness for university e-learning environments. *The Internet and Higher Education*, *25*, 1–10.

Pearson Foundation (2011). *Pearson Foundation community college student survey: Summary of California results*. Retrieved from http://www.faccc.org/wp-content/uploads/2014/11/ccc_student_survey.pdf

Ramlo, S. (2017). Student views regarding online freshmen physics courses. *Research in Science & Technological Education*, *35*(4), 461-476.

Rheinheimer, D. C., Grace-Odeleye, B., Francois, G. E., & Kusorgbor, C. (2010). Tutoring: A Support Strategy for At-Risk Students. *Learning Assistance Review, 15*(1), 23-34.

Rovai, A. P. (2003). In search of higher persistence rates in distance education online programs. *The Internet and Higher Education*, *6*(1), 1-16.

Scott-Clayton, J. (2015). The Shapeless River. In B. L. Castleman, S. Schwartz, & S. Baum (Eds.), *Decision making for student success: Behavioral insights to improve college access and persistence*. Abingdon, UK: Routledge.

Shapiro, D., Dundar, A., Wakhungu, P. K., Yuan, X., Nathan, A., & Hwang, Y. (2016). Time to degree: A national view of the time enrolled and elapsed for associate and bachelor's degree earners. *Signature Report*, (11).

Shea, P., & Bidjerano, T. (2014). Does online learning impede degree completion? A national study of community college students. *Computers & Education*, *75*, 103-111.

Shea, P., & Bidjerano, T. (2018). Online Course Enrollment in Community College and Degree Completion: The Tipping Point. *The International Review of Research in Open and Distributed Learning*, *19*(2), 282–293. https://doi.org/10.19173/irrodl.v19i2.3460

Sianesi, B., & Reenen, J. V. (2003). The returns to education: Macroeconomics. *Journal of Economic Surveys, 17*(2), 157–200.

Sin, K., & Muthu, L. (2015). Application of big data in education data mining and learning analytics--A literature review. *ICTACT Journal on Soft Computing, 5*(4), 1035-1049.

Smith, K., & Byrd, C. N. (2015). 2014 Joint Statistical Report Summary. *Summer Academe: A Journal of Higher Education*, 9.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65,* 557–586.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. Identification and inference for econometric models: Essays in honor of Thomas Rothenberg, 80(4.2), 1.

Stone, C., O'Shea, S., May, J., Delahunty, J., & Partington, Z. (2016). Opportunity through online learning: Experiences of first-in-family students in online open-entry higher education. *Australian Journal of Adult Learning, 56*(2), 146-169.

Sublett, C. (2019). Examining distance education coursetaking and time-to-completion among community college students. *Community College Journal of Research and Practice, 43*(3), 201-215.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*(1), 89–125.

Tinto, V. (1987). *Leaving college*. Chicago, IL: University of Chicago Press.

Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago, IL: University of Chicago Press

U.S. Department of Education. (2017). *Digest of Education Statistics 2017.* Retrieved from: https://nces.ed.gov/programs/digest/d17/tables/dt17_326.10.asp

U.S. Department of Health & Human Services (2021). *U.S. Federal Poverty Guidelines Used to Determine Financial Eligibility of Certain Federal Programs*. Retrieved from https://aspe.hhs.gov/poverty-guidelines

University of California (2021). *Admission by exam*. Retrieved from https://admission.universityofcalifornia.edu/admission-requirements/freshman-requirements/admission-by-exam.html.

Vanslambrouck, S., Zhu, C., Lombaerts, K., Philipsen, B., & Tondeur, J. (2018). Students' motivation and subjective task value of participating in online and blended learning environments. *The Internet and Higher Education*, *36*, 33-40.

Vo, H. M., Zhu, C., & Diep, N. A. (2017). The effect of blended learning on student performance at course-level in higher education: A meta-analysis. *Studies in Educational Evaluation*, *53*, 17–28. https://doi.org/10.1016/j.stueduc.2017.01.002

Volkwein, J. F., & Lorang, W. G. (1996). Characteristics of extenders: Full-time students who take light credit loads and graduate in more than four years. *Research in Higher Education, 37*(1), 43-68.

Waschull, S. B. (2001). The online delivery of psychology courses: Attrition, performance, and evaluation. *Teaching of Psychology*, *28*(2), 143–147.

Watson, J., & Gemin, B. (2008). *Using Online Learning for At-Risk Students and Credit Recovery. Promising Practices in Online Learning.* Vienna, VA: North American Council for Online Learning.

Williams, P. E., & Hellman, C. M. (2004). Differences in self-regulation for online learning between first- and second-generation college students. *Research in Higher Education, 45*(1), 71–82.

Witteveen, D., & Attewell, P. (2021). Delayed time-to-degree and post-college earnings. *Research in Higher Education*, *62*, 230–257.

Wong, L. F., & Trinidad, S. G. (2004). Using Web-based distance learning to reduce cultural distance. *The Journal of Interactive Online Learning*, *3*(1), 1-13.

Xu, D., & Jaggars, S. (2011a). *Online and hybrid course enrollment and performance in Washington State community and technical colleges*. CCRC Working Paper No. 31. Community College Research Center, Columbia University.

Xu, D., & Jaggars, S. S. (2011b). The effectiveness of distance education across Virginia's community colleges: Evidence from introductory college-level Math and English courses. *Educational Evaluation and Policy Analysis*, *33*(3), 360–377.

Xu, D., & Jaggars, S. S. (2013). The impact of online learning on students' course outcomes: Evidence from a large community and technical college system. *Economics of Education Review, 37*, 46–57. https://doi.org/10.1016/j.econedurev.2013.08.001

Xu, D., & Jaggars, S. S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *The Journal of Higher Education, 85*(5), 633–659. https://doi.org/10.1080/00221546.2014.11777343

Xu, D., Solanki, S., McPartlan, P., & Sato, B. (2018). EASEing students into college: The impact of multidimensional support for underprepared students. *Educational Researcher, 47*(7), 435-450.

Xu, D., & Xu, Y. (2019). *The promises and limits of online higher education: Understanding how distance education affects access, cost, and quality*. American Enterprise Institute. Retrieved from http://www.aei.org/publication/the-promises-and-limits-of-online-higher-education/

Yates, K. J. (2010). *Graduation Rates: A comparison of first-time, full-time freshmen who entered a community college prepared and those who entered underprepared for college-level work*. Unpublished doctoral dissertation. Retrieved from https://dc.etsu.edu/cgi/viewcontent.cgi?article=3029&context=etd

Yeboah, A. K., & Smith, P. (2016). Relationship between minority students online learning experiences and academic performance. *Online Learning*, *20*(4), 245–271. http://dx.doi.org/10.24059/olj.v20i4.577.

You, J. W. (2016). Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education*, *29*, 23–30.

Yue, H., & Fu, X. (2017). Rethinking graduation and time to degree: A fresh perspective. *Research in Higher Education, 58*(2), 184-213.

Zarifa, D., Kim, J., Seward, B., & Walters, D. (2018). What's taking you so long? Examining the effects of social class on completing a bachelor's degree in four years. *Sociology of Education, 91*(4), 290–322. https://doi.org/10.1177/0038040718802258F

Zhang, G., Anderson, T. J., Ohland, M. W., & Thorndyke, B. R. (2004). Identifying factors influencing engineering student graduation: A longitudinal and cross-institutional study. *Journal of Engineering Education*, *93*(4), 313-320.

Zhou, N., Fischer, C., Rodriguez, F., Warschauer, M, & King, S. (2019). Exploring how enrolling in an online organic chemistry preparation course relates to students' self-efficacy. *Journal of Computing in Higher Education*. Advance online publication. https://doi.org/10.1007/s12528-019-09244-9

Tables and Figures

Table 1. Descriptive cohort and student information.

	Full sample		Sample of graduated in 6 years	
	Mean / %	SD	Mean / %	SD
Cohort year				
2009	0.291	/	0.291	/
2010	0.328	/	0.331	/
2011	0.381	/	0.378	/
Transfer student	0.080	/	0.082	/
Female	0.623	/	0.628	/
Student's racial/ethnic background				
White	0.160	/	0.159	/
Black	0.027	/	0.026	/
Asian	0.608	/	0.617	/
Hispanic	0.199	/	0.192	/
Native American	0.006	/	0.006	/
California resident	0.953	/	0.955	/
First-generation college student	0.406	/	0.403	/
Low-income student	0.324	/	0.319	/
English language learner	0.266	/	0.262	/
Admission score	190.177	36.58	191.006	36.12
Number of passed AP exams	2.809	2.58	2.849	2.58
Number of summer terms	1.905	1.28	1.983	1.26
Number of major-required courses in summer	1.328	1.93	1.388	1.95
Number of major-required courses TAKEN online	0.091	0.320	0.096	0.328
Number of major-required lower division courses TAKEN online	0.010	0.102	0.010	0.104
Four-year graduation	0.805	0.396	0.862	0.345
Six-year graduation	0.934	0.248	1	0
Time to degree	/	/	3.714	0.683
Cohort size	691.027	505.06	681.217	499.370
N	10,572		9,878	

Notes. First-generation college students were those whose parents do not hold a Bachelor's degree. Low-income status was coded based on family household income and household size using 185% of the U.S. poverty line, similar to federal guidelines for determining financial eligibility to federal programs (U.S. Department of Health & Human Services, 2021). Student admission score (on a 60-300 scale) is based on students' ACT/SAT examination results, conversation rates are provided by the university (University of California, 2021). Cohort size is the number of students in the major in the same starting cohort. Number of summer terms refers to the number of summer terms in which the student took at least one course. Data on two samples are presented: the sample of students from the three cohorts who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878).

Table 2. The associations between student characteristics and course offering

	Cohorts from all thirteen majors		Cohorts from all thirteen majors, excluding public health major	
	All major-required courses OFFERED online	Major-required lower division courses OFFERED online	All major-required courses OFFERED online	Major-required lower division courses OFFERED online
Female	-0.529	-0.515	-0.257	-0.344
	(0.60)	(0.50)	(0.51)	(0.48)
Student's racial/ethnic background (vs. White)				
Black	0.252+	0.281*	0.049	0.140
	(0.14)	(0.12)	(0.14)	(0.13)
Asian	0.880	0.361	0.178	-0.307
	(0.63)	(0.53)	(0.60)	(0.56)
Hispanic	0.616	0.762	0.041	0.258
	(0.53)	(0.44)	(0.53)	(0.49)
Native	0.130	0.035	0.166	0.014
	(0.13)	(0.11)	(0.12)	(0.11)
California resident	-0.105	-0.466	-0.019	-0.494
	(0.41)	(0.34)	(0.36)	(0.34)
First-generation college student	0.544+	0.480+	0.455	0.381
	(0.28)	(0.24)	(0.25)	(0.24)
Low-income student	0.163	0.425	-0.026	0.347
	(0.36)	(0.30)	(0.32)	(0.29)
English language learner	0.146	-0.072	0.272	-0.043
	(0.57)	(0.47)	(0.49)	(0.45)
Admission score	1.080+	1.689**	0.488	1.284*
	(0.60)	(0.51)	(0.60)	(0.56)
Number of passed AP exams	0.275	0.005	-0.362	-0.389
	(0.53)	(0.44)	(0.48)	(0.45)
Cohort size	0.253	-0.289	-0.147	-0.643
	(0.60)	(0.50)	(0.54)	(0.50)
Cohort fixed effects	X	X	X	X
Major fixed effects	X	X	X	X
F-statistic	1.41	4.12***	0.96	2.62+
N	39	39	36	36
R-squared	0.956	0.969	0.971	0.975

Note. First-generation college students were those whose parents do not hold a Bachelor's degree. Low-income status was coded based on family household income and household size using 185% of the U.S. poverty line, similar to federal guidelines for determining financial eligibility to federal programs (U.S. Department of Health & Human Services, 2021). Student admission score (on a 60-300 scale) is based on students' ACT/SAT examination results, conversation rates are provided by the university (University of California, 2021). Cohort size is the number of students in major in same starting cohort. Number of summer terms in which the student took at least one course and number of major-required courses taken in summer are included as covariates in our analysis because a sizable proportion of online courses are offered over the summer. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Courses that would advance student progress towards school and departmental major requirements were treated as a "major-required" course. Two samples are used in the analysis: cohorts from all thirteen majors (N=39) and cohorts from all thirteen majors, excluding public health major (N=36). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Relationship between online course offering and graduation rates and time-to-degree

	OLS Linear Regression with major and cohort fixed effects					
	Four-year graduation		Six-year graduation		Time-to-degree	
All major-required courses OFFERED online in first four year	1.233** (0.42)		0.234 (0.15)		-1.310+ (0.66)	
Major-required lower division courses OFFERED online in first year		1.232** (0.39)		0.208 (0.15)		-1.645** (0.58)
Student characteristics	X	X	X	X	X	X
Major fixed effects	X	X	X	X	X	X
Cohort fixed effects	X	X	X	X	X	X
N	10,572	10,572	10,572	10,572	9,878	9,878

Note. Ordinary least square (OLS) linear regression models estimating the associations between the percent of major-required courses OFFERED online and student degree outcomes (panel A). The covariates in the models include both student and cohort characteristics listed in Table 1. Models in panel B further control for major fixed effects and cohort fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4. Relationship between online course taking and four- and six-year graduation rates.

	First-stage analysis		Second-stage analysis	
	All major-required courses TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation
Instrument: All major-required courses OFFERED online in first four years	0.086** (0.03)			
Instrument: All major-required lower division courses OFFERED online in first years		0.138*** (0.02)		
Instrumented variable: All major-required courses TAKEN online in first four years			14.375+ (7.78)	2.735 (1.02)
Instrumented variable: Major-required lower division courses TAKEN online in first year			8.955*** (2.66)	1.511 (1.04)
Student characteristics	X	X	X	X
Major FE	X	X	X	X
Cohort FE	X	X	X	X
F-statistic of IV	8.526	74.823		
N	10,572	10,572	10,572	10,572

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. The sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) is used. We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. Standard errors are clustered at the major by cohort and individual levels. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. Relationship between online course taking and student time-to-degree.

	First-stage analysis		Second-stage analysis
	All major-required courses TAKEN online	Major-required lower division courses TAKEN online	Time-to-degree
Instrument: All major-required courses OFFERED online in first four years	0.085** (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.137*** (0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years			-15.463 (11.11)
Instrumented variable: Major-required lower division courses TAKEN online in first year			-11.976** (3.85)
Student characteristics	X	X	X
Major FE	X	X	X
Cohort FE	X	X	X
F-statistic of IV	8.009	76.212	
N	9,878	9,878	9,878

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. The restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878) is used. We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first years with major-required lower division courses OFFERED online in first years to estimate its effect. Standard errors are clustered at the major by cohort and individual levels. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6. Heterogeneity analysis of the relationships of taking online courses.

	Major-required online course TAKEN	Four-year graduation	Six-year graduation	Major-required online course TAKEN	Time-to-degree
Panel A	**First-generation college student status**				
Instrument: All major-required courses OFFERED online in first four years	0.091** (0.03)			0.090** (0.03)	
Instrument: All major-required courses OFFERED online in first four years*First-generation college student	-0.011 (0.01)			-0.012 (0.01)	
Instrument: Major-required lower division courses OFFERED online in first year	0.133*** (0.02)			0.132*** (0.02)	
Instrument: Major-required lower division courses OFFERED online in first year*First-generation college student	0.010 (0.01)			0.012 (0.01)	
Instrumented variable: All major-required courses TAKEN online in first four years		13.973* (7.65)	2.332 (2.02)		-16.266 (10.69)
Instrumented variable: All major-required courses TAKEN online in first four years*First-generation college student		1.180 (1.61)	1.184 (0.99)		2.282 (1.90)
Instrumented variable: Major-required lower division courses TAKEN online in first year		9.408** (3.04)	1.223 (1.20)		-14.623*** (4.19)
Instrumented variable: Major-required lower division courses TAKEN online in first year*First-generation college student		-0.975 (1.56)	0.618 (0.93)		5.465** (1.81)
Student characteristics	X	X	X	X	X
Major FE	X	X	X	X	X
Cohort FE	X	X	X	X	X
N	10,572	10,572	10,572	9,878	9,878
Panel B	**Low-income status**				
Instrument: All major-required courses OFFERED online in first four years	0.086** (0.03)			0.081** (0.03)	
Instrument: All major-required courses OFFERED online in first four years*Low-income	0.009 (0.01)			0.009 (0.01)	
Instrument: Major-required lower division courses OFFERED online in first year	0.116*** (0.01)			0.112*** (0.01)	
Instrument: Major-required lower division courses OFFERED online in first year*Low- income	0.051* (0.02)			0.060** (0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years		15.492+ (8.17)	2.206 (2.16)		-18.572+ (11.18)
Instrumented variable: All major-required courses TAKEN online in first four years*Low-income		-2.811 (2.98)	1.330 (0.88)		8.204* (3.83)
Instrumented variable: Major-required		11.624***	1.329		-18.489***

lower division courses TAKEN online in first year		(3.35)	(1.32)		(4.85)
Instrumented variable: Major-required lower division courses TAKEN online in first year*Low-income		-5.176**	0.352		12.205*
		(2.20)	(0.85)		(4.19)
Student characteristics	X	X	X	X	X
Major FE	X	X	X	X	X
Cohort FE	X	X	X	X	X
N	10,572	10,572	10,572	9,878	9,878
Panel C			**Academic preparation**		
Instrument: All major-required courses OFFERED online in first four years	0.083**			0.081**	
	(0.03)			(0.03)	
Instrument: All major-required courses OFFERED online in first four years*Weak academic preparation	0.005			0.006	
	(0.02)			(0.02)	
Instrument: Major-required lower division courses OFFERED online in first year	0.112***			0.112***	
	(0.02)			(0.02)	
Instrument: Major-required lower division courses OFFERED online in first year*Weak academic preparation	0.042+			0.042	
	(0.02)			(0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years		12.506	1.075		-23.136+
		(8.51)	(2.27)		(13.51)
Instrumented variable: All major-required courses TAKEN online in first four years*Weak academic preparation		2.488	2.198+		10.115**
		(2.48)	(1.26)		(3.34)
Instrumented variable: Major-required lower division courses TAKEN online in first year		9.823**	0.996		-20.536***
		(3.30)	(1.38)		(5.39)
Instrumented variable: Major-required lower division courses TAKEN online in first year*Weak academic preparation		-1.568	0.874		15.016***
		(2.91)	(1.19)		(3.94)
Student characteristics	X	X	X	X	X
Major FE	X	X	X	X	X
Cohort FE	X	X	X	X	X
N	10,572	10,572	10,572	9,878	9,878

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. The F statistics of the instrumental variable of all major-required courses offered online in first four years range from 6.300 to 10.240 across the subgroups examined, with specific values for non-first-generation students, first-generation students, non-low-income students, low-income students, students with strong academic preparation, and students with weak academic preparation being 10.240, 6.300, 7.236, 9.734, 7.076, and 8.468, respectively. The F statistics of the instrumental variable of major-required lower division courses taken online in first year range from 49.985 to 68.558 across the subgroups examined, with specific values for non-first-generation students, first-generation students, non-low-income students, low-income students, students with strong academic preparation, and students with weak academic preparation being 68.558, 60.063, 67.076, 49.985, 27.458, and 64.803, respectively. Standard errors are clustered at the major by cohort and individual levels. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

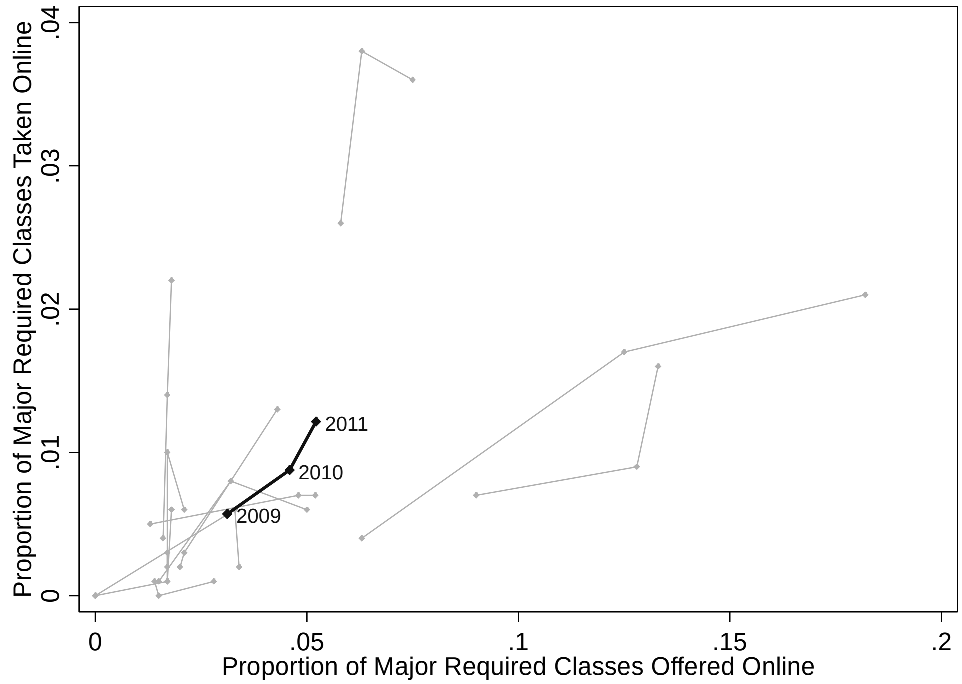

Figure 1. Proportions of all major-required courses offered and taken online in students' first four years by major and cohort for each major (grey lines) and aggregated (black line).

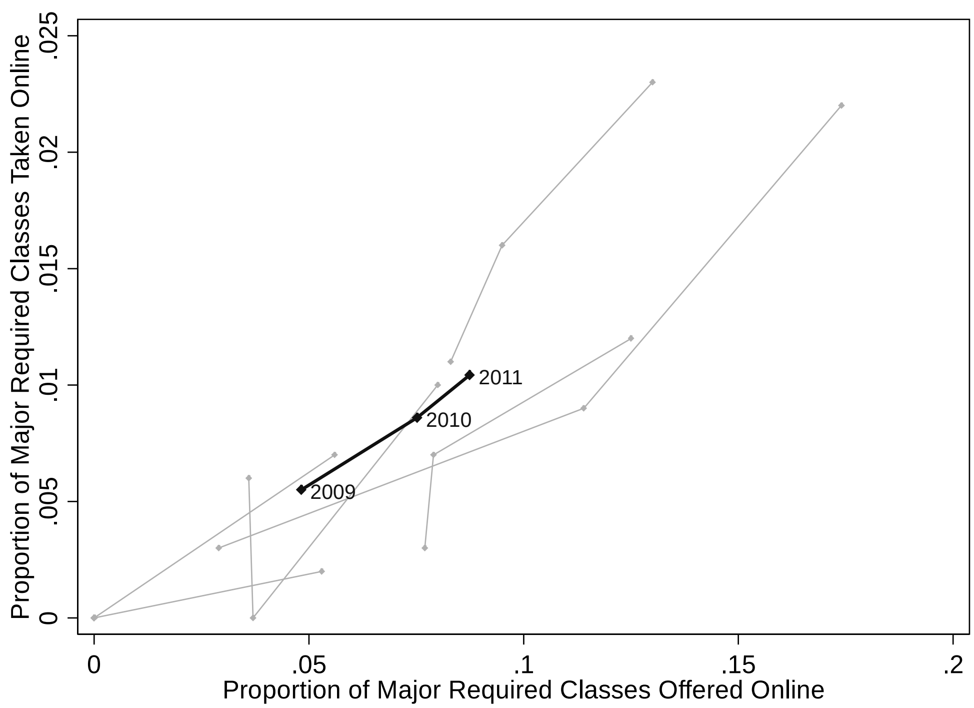

Figure 2. Proportion of major-required lower division courses offered and taken online in students' first year by major and cohort for each major (grey lines) and aggregated (black line).

Appendix

Table A1. Percent of all major-required courses offered and taken online in students' first four years by major and cohort.

	2009			2010			2011			Total		
	Major-required courses OFFERED online	Major-required courses TAKEN online	Cohort size	Major-required courses OFFERED online	Major-required courses TAKEN online	Cohort size	Major-required courses OFFERED online	Major-required courses TAKEN online	Cohort size	Major-required courses OFFERED online	Major-required courses TAKEN online	Cohort size
Computer Science	1.3%	0.5%	63	4.8%	0.7%	92	5.2%	0.7%	197	4.4%	0.6%	352
Chemistry	1.7%	0.2%	96	2.1%	0.6%	108	1.7%	1.0%	129	1.8%	0.6%	333
Mathematics	1.7%	0.1%	76	1.7%	0.3%	111	1.7%	0.1%	120	1.7%	0.2%	307
Psychology & Social Behavior	1.6%	0.4%	253	1.7%	1.4%	359	1.8%	2.2%	444	1.7%	1.3%	1,056
Biological Sciences	0.0%	0.0%	974	0.0%	0.0%	991	0.0%	0.0%	1026	0.0%	0.0%	2,991
Business Economics	0.0%	0.0%	315	3.4%	0.2%	335	3.3%	0.6%	466	2.4%	0.3%	1,116
Psychology	1.5%	0.0%	238	2.8%	0.1%	213	1.4%	0.1%	229	1.9%	0.1%	680
Political Science	1.5%	0.1%	233	3.2%	0.8%	256	5.0%	0.6%	291	3.4%	0.5%	780
Public Health Science	9.0%	0.7%	233	12.8%	0.9%	322	13.3%	1.6%	249	11.9%	1.1%	804
Public Health Policy	6.3%	0.4%	117	12.5%	1.7%	161	18.2%	2.1%	196	13.3%	1.4%	474
Criminology	0.0%	0.0%	171	1.7%	0.1%	223	1.8%	0.6%	272	1.3%	0.2%	666
Sociology	5.8%	2.6%	180	7.5%	3.6%	160	6.3%	3.8%	238	6.5%	3.3%	578
Economics	2.1%	0.3%	131	2.0%	0.2%	137	4.3%	1.3%	167	2.9%	0.6%	435
Total	1.8%	0.4%	3,080	3.5%	0.8%	3,468	3.8%	1.1%	4,024	3.1%	0.8%	10,572

Note. Data on the percent of all major-required courses offered and taken online in students' first four years and cohort size is presented by major and cohort for students from the three cohorts who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six). Courses that would advance student progress towards school and departmental major requirements were treated as a "major-required" course. Information on major requirements were accessed from the publicly available general catalogue.

Table A2. Percent of major-required lower division courses offered and taken online in students' first year by major and cohort.

	2009			2010			2011			Total		
	Major-required lower division courses OFFERED online	Major-required lower division courses TAKEN online	Cohort size	Major-required lower division courses OFFERED online	Major-required lower division courses TAKEN online	Cohort size	Major-required lower division courses OFFERED online	Major-required lower division courses TAKEN online	Cohort size	Major-required lower division courses OFFERED online	Major-required lower division courses TAKEN online	Cohort size
Computer Science	3.7%	0.0%	63	3.6%	0.6%	92	8.0%	1.0%	197	6.1%	0.5%	352
Chemistry	0.0%	0.0%	96	0.0%	0.0%	108	5.6%	0.7%	129	2.2%	0.2%	333
Mathematics	0.0%	0.0%	76	0.0%	0.0%	111	5.3%	0.2%	120	2.1%	0.1%	307
Psychology & Social Behavior	0.0%	0.0%	253	0.0%	0.0%	359	0.0%	0.0%	444	0.0%	0.0%	1,056
Biological Sciences	0.0%	0.0%	974	0.0%	0.0%	991	0.0%	0.0%	1,026	0.0%	0.0%	2,991
Business Economics	0.0%	0.0%	315	0.0%	0.0%	335	0.0%	0.0%	466	0.0%	0.0%	1,116
Psychology	0.0%	0.0%	238	0.0%	0.0%	213	0.0%	0.0%	229	0.0%	0.0%	680
Political Science	0.0%	0.0%	233	0.0%	0.0%	256	0.0%	0.0%	291	0.0%	0.0%	780
Public Health Science	7.9%	0.7%	233	7.7%	0.3%	322	12.5%	1.2%	249	9.2%	0.7%	804
Public Health Policy	2.9%	0.3%	117	11.4%	0.9%	161	17.4%	2.2%	196	11.8%	1.1%	474
Criminology	0.0%	0.0%	171	0.0%	0.0%	223	0.0%	0.0%	272	0.0%	0.0%	666
Sociology	8.3%	1.1%	180	13.0%	2.3%	160	9.5%	1.6%	238	10.1%	1.7%	578
Economics	0.0%	0.0%	131	0.0%	0.0%	137	0.0%	0.0%	167	0.0%	0.0%	435
Total	1.3%	0.1%	3,080	1.9%	0.2%	3,468	2.9%	0.4%	4,024	2.1%	0.2%	10,572

Note. Data on the percent of major-required lower division courses offered and taken online in students' first year and cohort size is presented by major and cohort for students from the three cohorts who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six). Courses that would advance student progress towards school and departmental major requirements were treated as a "major-required" course. Information on major requirements were accessed from the publicly available general catalogue.

Table A3. Associations between student characteristics, degree outcomes, and online course taking.

	Four-year graduation	Time-to-degree	All major-required courses TAKEN online in first four years	Major-required lower division courses TAKEN online in first year
Female	0.072***	-0.007	0.002**	0.000
	(0.01)	(0.02)	(0.00)	(0.00)
Student's racial/ethnic background (vs. White)				
Black	-0.034	0.070	0.001	0.002
	(0.03)	(0.05)	(0.00)	(0.00)
Asian	0.037**	-0.023	-0.001	0.001
	(0.01)	(0.02)	(0.00)	(0.00)
Hispanic	-0.070***	0.214***	0.001	0.001
	(0.02)	(0.03)	(0.00)	(0.00)
Native	-0.044	0.067	0.004	0.002
	(0.06)	(0.11)	(0.01)	(0.00)
California resident	0.068**	-0.028	-0.001	-0.003+
	(0.03)	(0.05)	(0.00)	(0.00)
First-generation college student	0.025*	0.013	-0.001	-0.000
	(0.01)	(0.02)	(0.00)	(0.00)
Low-income student	-0.059***	0.090***	0.000	0.001
	(0.01)	(0.02)	(0.00)	(0.00)
English language learner	-0.022+	0.030	-0.001	-0.001+
	(0.01)	(0.02)	(0.00)	(0.00)
Admission score	0.001**	0.002***	0.000*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Number of passed AP exams	0.006*	0.004	-0.000+	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Number of summer terms	-0.007	0.208***	0.001***	-0.000*
	(0.01)	(0.01)	(0.00)	(0.00)
Number of major-required courses in summer	-0.004	-0.023***	0.002***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Major FE	X	X	X	X
Cohort FE	X	X	X	X
F statistics	18.54***	72.05***	16.27***	3.74***
N	10,572	9,878	10,572	10,572
R-squared	0.052	0.156	0.127	0.031

Note. First-generation college students were those whose parents do not hold a Bachelor's degree. Low-income status was coded based on family household income and household size using 185% of the U.S. poverty line, similar to federal guidelines for determining financial eligibility to federal programs (U.S. Department of Health & Human Services, 2021). Student admission score (on a 60-300 scale) is based on students' ACT/SAT examination results, conversation rates are provided by the university (University of California, 2021). Cohort size is the number of students in the major in the same starting cohort. Number of summer terms in which the student took at least one course and number of major-required courses taken in summer are included as covariates in our analysis because a sizable proportion of online courses are offered over the summer. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Courses that would advance student progress towards school and departmental major requirements were treated as a "major-required" course. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A4. Associations of online course taking with student graduation rates and time-to-degree

Panel A	OLS Linear Regression					
	Four-year graduation		Six-year graduation		Time-to-degree	
All major-required courses TAKEN online in first four years	-0.500** (0.18)		0.158* (0.08)		1.434*** (0.24)	
Major-required lower division courses TAKEN online in first year		0.099 (0.13)		0.002 (0.05)		-0.624** (0.26)
Student characteristics	X	X	X	X	X	X
N	10,572	10,572	10,572	10,572	9,878	9,878
Panel B	**OLS Linear Regression with major and cohort fixed effects**					
	Four-year graduation		Six-year graduation		Time-to-degree	
All major-required courses TAKEN online in first four years	-0.669*** (0.19)		-0.002 (0.08)		1.602*** (0.27)	
Major-required lower division courses TAKEN online in first year		0.108 (0.13)		-0.002 (0.05)		-0.702** (0.27)
Student characteristics	X	X	X	X	X	X
Major fixed effects	X	X	X	X	X	X
Cohort fixed effects	X	X	X	X	X	X
N	10,572	10,572	10,572	10,572	9,878	9,878

Note. Ordinary least square (OLS) linear regression models estimating the associations between the percent of major-required courses taken online and student degree outcomes (panel A). The covariates in the models include both student and cohort characteristics listed in Table 1. Models in panel B further control for major fixed effects and cohort fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878). + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A5. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time to degree excluding public health policy major

	Full Sample				Students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.073 (0.05)				0.073 (0.05)		
Instrument: Major-required lower division courses OFFERED online in first year		0.146*** (0.02)				0.145*** (0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years			10.906 (12.81)	5.346 (5.62)			-8.258 (19.35)
Instrumented variable: Major-required lower division courses TAKEN online in first year			10.220+ (5.30)	2.557 (2.29)			-16.286* (7.45)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	2.190	44.489			2.016	42.641	
N	10,098	10,098	10,098	10,098	9,408	9,408	9,408

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors except public health policy major (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,098) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors except public health policy major (N = 9,408). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A6. Relationships between percent of students who switched into a major of a given cohort and online course offering in a major

	All analytic sample		Students who graduated in 6 years	
All major-required courses OFFERED online in first four years	0.002 (0.02)		0.005 (0.02)	
Major-required lower division courses OFFERED online in first year		-0.007 (0.01)		-0.009 (0.01)
Major fixed effects	X	X	X	X
Cohort fixed effects	X	X	X	X
N	39	39	39	39
R-squared	0.957	0.957	0.947	0.948

Note. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A7. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time to degree for students who started and finished in one of the analyzed majors

	Full Sample				Students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	-0.017 (0.03)				-0.021 (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.030 (0.06)				0.028 (0.06)	
Instrumented variable: All major-required courses TAKEN online in first four years			19.897 (50.55)	-8.654 (38.98)			-12.460 (77.09)
Instrumented variable: Major-required lower division courses TAKEN online in first year			25.148 (51.13)	11.933 (25.03)			-59.333 (123.48)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	0.360	0.281			0.423	0.212	
N	3,482	3,482	3,482	3,482	2,953	2,953	2,953

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who started and completed their program of study in one of these thirteen majors (N = 3,482) and the restricted sample of students who started and successfully graduated within six years with one of these thirteen majors (N = 2,953). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A8. Associations of online course offering with summer course enrollment

	Number of summer terms enrolled		Number of major-required courses taken over the summer	
All major-required courses OFFERED online in first four years	-1.581***		0.237	
	(0.38)		(0.84)	
Major-required lower division courses OFFERED online in first year		-1.563***		-1.480
		(0.40)		(1.04)
Female	0.021	0.021	-0.047	-0.048
	(0.03)	(0.03)	(0.03)	(0.03)
Student's racial/ethnic background (vs. White)				
Black	0.618***	0.619***	0.342**	0.345**
	(0.09)	(0.09)	(0.11)	(0.11)
Asian	0.509***	0.508***	0.278***	0.277***
	(0.05)	(0.05)	(0.06)	(0.06)
Hispanic	0.261***	0.261***	0.175**	0.175**
	(0.05)	(0.05)	(0.06)	(0.06)
Native	0.123	0.118	0.205	0.204
	(0.15)	(0.15)	(0.20)	(0.20)
California resident	-0.026	-0.027	-0.074	-0.076
	(0.08)	(0.08)	(0.08)	(0.08)
First-generation college student	-0.032	-0.032	0.051	0.051
	(0.03)	(0.03)	(0.04)	(0.04)
Low-income student	0.060	0.061	0.094*	0.095*
	(0.04)	(0.04)	(0.04)	(0.04)
English language learner	-0.006	-0.006	0.017	0.017
	(0.04)	(0.04)	(0.04)	(0.04)
Admission score	-0.001*	-0.001*	-0.002*	-0.002*
	(0.00)	(0.00)	(0.00)	(0.00)
Number of passed AP exams	-0.024**	-0.024**	-0.004	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)
Cohort size	0.000	0.000	0.001*	0.001*
	(0.00)	(0.00)	(0.00)	(0.00)
Major FE	X	X	X	X
Cohort FE	X	X	X	X
N	10572	10572	10572	10572
R-squared	0.123	0.123	0.403	0.404

Note. First-generation college students were those whose parents do not hold a Bachelor's degree. Low-income status was coded based on family household income and household size using 185% of the U.S. poverty line, similar to federal guidelines for determining financial eligibility to federal programs (U.S. Department of Health & Human Services, 2021). Student admission score (on a 60-300 scale) is based on students' ACT/SAT examination results, conversation rates are provided by the university (University of California, 2021). Cohort size is the number of students in major in same starting cohort. Number of summer terms in which the student took at least one course and number of major-required courses taken in summer are included as covariates in our analysis because a sizable proportion of online courses are offered over the summer. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Courses that would advance student progress towards school and departmental major requirements were treated as a "major-required" course. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572)
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A9. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time to degree excluding summer course enrollment as controls

	Full Sample				Students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.084** (0.03)				0.082** (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.136*** (0.02)				0.136*** (0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years			14.751+ (7.92)	1.862 (2.04)			-21.107 (12.91)
Instrumented variable: Major-required lower division courses TAKEN online in first year			9.167*** (2.65)	0.974 (1.07)			-14.609*** (3.85)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	8.468	73.445			7.508	74.650	
N	10,572	10,572	10,572	10,572	9,878	9,878	9,878

Note. All models include student covariates (cf. Table 1) except for number of summer terms enrolled and number of major-required courses taken over the summer, major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,572) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A10. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time to degree randomly selecting only one observation per student

	Sample of unique students				Sample of unique students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.066* (0.03)				0.063* (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.113*** (0.01)				0.111*** (0.01)	
Instrumented variable: All major-required courses TAKEN online in first four years			15.127 (9.86)	4.776 (4.07)			-14.309 (13.99)
Instrumented variable: Major-required lower division courses TAKEN online in first year			10.638** (3.74)	2.297 (1.62)			-13.109** (5.02)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	4.928	57.760			4.537	93.316	
N	7,900	7,900	7,900	7,900	7,252	7,252	7,252

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors except public health policy major (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,098) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors except public health policy major (N = 9,408). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A11. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time to degree including sample weight

	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.059* (0.03)				0.057+ (0.03)		
Instrument: Major-required lower division courses OFFERE online in first year		0.107*** (0.01)				0.104*** (0.01)	
Instrumented variable: All major-required courses TAKEN online in first four years			20.502 (13.20)	5.845 (4.77)			-18.477 (17.81)
Instrumented variable: Major-required lower division courses TAKEN online in first year			12.708*** (3.42)	2.518 (1.69)			-16.887** (5.45)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	4.244	60.684			3.725	62.568	
N	10,572	10,572	10,572	10,572	9,878	9,878	9,878

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors except public health policy major (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six; N = 10,098) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors except public health policy major (N = 9,408). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A12. Estimates of the relationship between online course taking and four- and six-year graduation rates and time-to-degree excluding transfer students

	Full Sample				Students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.087**				0.086**		
	(0.03)				(0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.136***				0.136***	
		(0.02)				(0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years			15.039+	3.034			-17.963+
			(8.02)	(1.94)			(9.23)
Instrumented variable: Major-required lower division courses TAKEN online in first year			8.830**	1.148			-9.735***
			(3.12)	(1.03)			(2.86)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	7.784	34.692			7.236	35.641	
N	9,724	9,724	9,724	9,724	9,064	9,064	9,064

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six) excluding transfer students (N = 9,724) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors excluding transfer students (N = 9,439). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A13. Estimates of the relationship between online course taking and student four- and six-year graduation rates and time-to-degree with dummy variable adjustment (instead of listwise deletion missing data approaches)

	Full Sample				Students who graduated in 6 years		
	First stage analysis		Second stage analysis		First stage analysis		Second stage analysis
	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Four-year graduation	Six-year graduation	All major-required online course TAKEN online	Major-required lower division courses TAKEN online	Time to degree
Instrument: All major-required courses OFFERED online in first four years	0.065* (0.03)				0.065* (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.138*** (0.03)				0.143*** (0.03)	
Instrumented variable: All major-required courses TAKEN online in first four years			14.512+ (8.56)	1.155 (1.88)			-11.420 (12.45)
Instrumented variable: Major-required lower division courses TAKEN online in first year			7.462*** (2.10)	0.980 (0.81)			-12.210*** (3.68)
Student characteristics	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X
Cohort FE	X	X	X	X	X	X	X
F-statistics of IV	6.503	24.900			6.003	25.000	
N	14,388	14,388	14,388	14,388	13,230	13,230	13,230

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. Two samples are used in the analysis: the sample of students who completed their program of study in one of these thirteen majors (i.e., graduated from the institution with the major, or were affiliated with the major at the end of year six) including students who had missing data on student covariates (N = 14,388) and the restricted sample of students who successfully graduated within six years with one of these thirteen majors including students who had missing data on student covariates (N = 13,230). We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first year with major-required lower division courses OFFERED online in first year to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A14. Relationships between online course taking and student terms-to-degree

	First-stage analysis		Second-stage analysis
	All major-required courses TAKEN online	Major-required lower division courses TAKEN online	Terms-to-degree
Instrument: All major-required courses OFFERED online in first four years	0.085** (0.03)		
Instrument: Major-required lower division courses OFFERED online in first year		0.137*** (0.02)	
Instrumented variable: All major-required courses TAKEN online in first four years			-39.921 (32.10)
Instrumented variable: Major-required lower division courses TAKEN online in first year			-32.051** (11.88)
Student characteristics	X	X	X
Major FE	X	X	X
Cohort FE	X	X	X
F-statistic of IV	8.009	76.213	
N	9,878	9,878	9,878

Note. All models include student covariates (cf. Table 1), major fixed effects, and cohort year fixed effects. Major FE refers to major fixed effects and Cohort FE refers to cohort fixed effects. The restricted sample of students who successfully graduated within six years with one of these thirteen majors (N = 9,878) is used. We instrument all major-required courses TAKEN online in first four years with all major-required courses OFFERED online in first four years to estimate its effect and instrument major-required lower division courses TAKEN online in first years with major-required lower division courses OFFERED online in first years to estimate its effect. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.