Online Course-taking and Student Outcomes
in California Community Colleges

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Cassandra M.D. Hart, Elizabeth Friedmann, and Michael Hill
University of California, Davis

This paper uses fixed effects analyses to estimate differences in student performance under online versus face-to-face course delivery formats in California's Community College system. On average, students have poorer outcomes in online courses, in terms of the likelihood of course completion; course completion with a passing grade; and receiving an A or B. These estimates are robust across estimation techniques, different groups of students, and different types of classes. Differences are especially acute in summer sessions, intersessions, non-transfer-eligible classes, and classes that enroll a smaller share of their students online. Differences in faculty characteristics only negligibly dampen the estimated relationships.

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The use of online courses is expanding rapidly at all levels of higher education. In the 1997-98 academic year, there were an estimated 1.08 million student-course enrollments in distance education undergraduate courses (Lewis, Snow, Farris, Levin, & Greene, 1999). By 2006-07, these figures had increased dramatically, to 9.8 million undergraduate distance education enrollments (Parsad & Lewis, 2008). The community college sector accounts for roughly half of these enrollments; public two-year colleges documented over 4.8 million enrollments in undergraduate distance learning courses in 2006-07 (Parsad & Lewis). Moreover, policymakers and administrators increasingly regard online education as important to the long-term strategy of their institutions (Allen & Seaman, 2014) because online course offerings are seen as an avenue to potentially cut costs while providing students with flexibility (Bartindale, 2013).[1] Notably, California Governor Jerry Brown has advocated for the expansion of online course offerings (Murphy, 2014), and offered grants for the state's Community College system to coordinate online course delivery across campuses (Wilson, 2013).

While the drive to incorporate online classes continues to gain momentum, much remains to be learned about how online course-taking affects student achievement. This paper uses a series of fixed effects models, including college-course fixed effects and individual fixed effects, to compare how students' course performance differs between online and face-to-face courses. We find, as others have, that students in face-to-face (FtF) courses outperform their peers in online courses across a number of outcomes. We rule out several explanations for this gap related to how students sort into classes. We further extend the literature by exploring faculty

[1] Administrators in large institutions are somewhat less optimistic about potential cost savings associated with online courses; only about 45% of administrators in institutions with enrollments of 15,000 students or greater said that it was likely or very likely that online courses would become considerably less expensive than face-to-face courses (Allen & Seaman, 2014).

characteristics as mediators of the relationship between online course enrollment and performance. We find that although online course enrollment is related to differences in the characteristics of faculty students are exposed to, these account for only a negligible portion of the performance decrement associated with online course-taking.

Finally, we explore heterogeneity of these impacts across different kinds of students and courses. We find that the negative relationship between online course-taking and performance are robust across different types of students and different types of courses, although we identify certain instances where the decrements associated with online course-taking are particularly pronounced. We find that the online performance decrement is especially acute in summer sessions, intersessions, non-transfer-eligible classes, and classes that enroll a relatively small share of their students online. Gaps are also more pronounced in Math and Humanities classes than in other subject areas. Our results have important implications for community college administrators and counselors as they consider how to use online courses as part of a suite of strategies to support students' needs.

Past literature

Because online courses are a relatively recent phenomenon in higher education, there is relatively little research on how students fare in these courses compared to in traditional face-to-face settings. A 2009 meta-analysis from the US Department of Education found that outcomes were generally positive for students enrolled in online or blended courses versus traditional class settings (Means, Toyama, Murphy, Bakia, & Jones, 2009). However, many of the studies analyzed in that meta-analysis compared online versus FtF delivery of brief training sessions (some as short as 15 minutes) rather than full courses conducted over the course of an academic term (Jaggars & Bailey, 2010); the latter setting is more relevant to postsecondary administrators considering whether to develop or expand online learning options. Moreover, among the seven studies that did compare term-length FtF courses with fully online alternatives, several were in subjects likely to be especially conducive to online learning (e.g., computer programming), and all were conducted at relatively selective universities (Jaggars & Bailey). Outcomes may be different in broad-access institutions that enroll students with generally lower levels of academic achievement and preparation. Furthermore, even well-conducted studies that compare FtF versus online course delivery in semester-long courses (Figlio, Rush, & Yin, 2013; Bowen, Chingos, Lack, & Nygren, 2014) generally focus on a small subset of classes (e.g., one specific microeconomics or statistics class) and are therefore unable to explore the heterogeneity of effects across different types of subject matters or other course characteristics.

A handful of studies have explored the outcomes of students across a wide set of courses in state community college settings (Xu & Jaggars, 2011; Kaupp, 2012; Xu & Jaggars, 2013; Xu & Jaggars, 2014; Johnson & Cuellar Mejia, 2014). These studies find that students in FtF courses outperform their peers in online courses, both in terms of course persistence and grades (Xu & Jaggars, 2011; Xu & Jaggars, 2013; Johnson & Cuellar Mejia, 2014), for most subgroups of students and in most subject areas (Xu & Jaggars, 2014). Using a variety of fixed-effects techniques, we find similar patterns.

We also extend past efforts in several ways. First, we explore a novel key factor that may explain the differences in performance in FtF versus online courses: faculty characteristics. Previous studies in predominantly face-to-face, four-year institutions have found that postsecondary instructors have modest, but measurable, effects on student performance in courses (Carrell & West, 2010; Hoffman & Oreopoulos, 2013), although findings are mixed as to the type of faculty qualifications that best promote student success. While several researchers have found that exposure to part-time, adjunct instructors is negatively associated with long-term outcomes like graduation rates (Ehrenberg & Zhang, 2005; Jacoby, 2006; Calcagno, Bailey, Jenkins, Kienzl, & Leinbach, 2008), persistence rates (Bettinger & Long, 2006), and performance in subsequent classes (Carrell & West, 2010), others have found benefits of having less-experienced or non-tenured instructors on contemporaneous course performance (Carrell & West, 2010), and on enrollments (Bettinger & Long, 2010) and performance (Figlio, Schapiro, & Soter, 2013) in subsequent courses in the same subject area.

Faculty qualifications may matter to online course-taking in two ways. First, if instructor qualifications are associated with student achievement and students in online courses are exposed to a systematically different mix of instructors than are their peers in FtF courses, these faculty qualifications may explain (or suppress) any observed differences in performance between the two formats. Second, faculty qualifications may matter differently in online versus FtF settings. For instance, if it is especially important in online settings for instructors to be able to anticipate confusion over material because online instructors lack the real-time, visual cues that would allow them to assess and react to student confusion during lectures (Bork & Rucks-Ahidiana, 2013), more experience teaching the subject matter may be more advantageous online. On the other hand, if tech-savvy is disproportionately developed in younger (generally less-experienced) instructors, they may be better equipped to promote online student success. We therefore study faculty characteristics as both mediating and moderating influences of the relationship between online course-taking and student performance.

In addition, we explore the heterogeneity in online vs. FtF performance based on several other novel course characteristics. For instance, past qualitative work suggests that some students try to take “easier” courses online because they think their performance will be more comparable to FtF sections when subject matter is less challenging (Jaggars, 2014); we therefore use proxy measures of course difficulty (student pass rates in face-to-face sections) to determine whether online-face-to-face-FtF performance gaps differ between more and less difficult classes. Because past qualitative work has also suggested that one of the challenges associated with online work is the greater self-motivation needed when the class is removed from the structure of face-to-face, regular meetings (Bork & Rucks-Ahidiana, 2013; Public Agenda, 2013; Jaggars, 2014), we were also interested in whether online course-taking might prove especially challenging in sessions outside of the normal academic calendar. That is, classes offered in the summer or during one-month intersession periods may be more challenging when another source of structure—having the bulk of one's peers attending classes at the same time—is loosened. Exploring such course-level factors that moderate student success in online versus FtF courses provides important information for community college administrators considering how to most effectively offer online course sections and support students enrolled in them.

Finally, we use routines that estimate two high-dimensional fixed effects at a time to simultaneously incorporate both individual and school-course fixed effects, providing the most rigorous effort to date to eliminate bias in online vs. face-to-face comparisons that may come from both individual and course-level factors.

California context

We explore the effects of online course-taking in California's community colleges. California is home to the nation's largest community college system, comprising 112 institutions educating over 2.3 million students per year (California Community Colleges Chancellor's Office [CCCCO], 2013a). Online course offerings have expanded steadily in California's community colleges. While distance education in some form has been offered since the 1980s, the content of distance courses was initially restricted to course offerings that were transferable to four-year institutions (CCCCO, 2013b). This policy was relaxed in 1994, and in 2002, the Board of Governors approved regulations changes to allow both credit and non-credit courses to be delivered virtually. As a result, distance education in California's community colleges grew from constituting 0.63% of course sessions in 1995-96 to 10.5% by 2011-12 (CCCCO, 2013b). Figure 1 plots the expansion of student enrollments in online courses in California community colleges from 2000-01 through 2011-12.

Campuses have latitude to set their own course offerings, and there is substantial variation in the extent to which campuses use online education. For instance, 56 of the 112 colleges in the system offered at least one degree or certificate fully through virtual delivery in 2011-12, including 296 Associate Degrees and 291 certificate programs (CCCCO, 2013b). As might be expected from the uneven adoption of fully-online certificate programs, online course-taking is not equally popular in all California Community Colleges. Two colleges had no online course enrollments among our sample students during the time period studied. Among those with some offerings, the share of enrollments observed in online courses ranged from 0.95% at Evergreen Valley College to 56.50% at Coastline Community College. In general, there are no specific qualifications for faculty to teach online; instead they only need to meet the minimum qualifications for faculty in the specific academic discipline. But faculty requirements for training to teach online also vary by campus. Results from a 2013 survey of online instructors show that 59 percent of college required training for instructors to teach online (Freitas & Gold, 2015). But 78 percent of colleges counted online training towards professional development credit and 21 counted the training towards unit credit for the salary schedule (Freitas & Gold, 2015).

California's community colleges offer two types of online courses. In an *asynchronous* format, instructors and student interactions are not primarily conducted in real-time. Instructors and students may e-mail each other or post to message boards, and lectures may be pre-recorded. Students access course content at their own pace. In a *synchronous* delivery format, instructors and students do not meet in the same place, but all access the course platform simultaneously during pre-arranged times and there is real-time interaction amongst the course participants. Asynchronous delivery is the more popular method; over 90% of virtual courses were conducted through asynchronous course delivery in the 2011-12 academic year (CCCCO, 2013b).

Analytic Method

Data and Sample

To determine how online course-taking is associated with student performance, we draw on data from the California Community College Chancellor's Office. Our sample constitutes students who are first-time entrants to the community college system in the 2008-09 academic year. We observe all course enrollments, course outcomes, student characteristics, and faculty characteristics for this cohort over 3,011,232 enrollments in 57,270 courses from 2008-09 through 2011-12.

We impose several sample restrictions. We drop physical education and fine arts courses, and courses offered for less than 1 (or greater than 5) credits. We include only courses taught in a face-to-face lecture or discussion formats, or through online formats elaborated below. In order to obtain a more homogenous sample, we want to compare students with relatively similar levels of education at the outset of their California Community College careers. We therefore exclude students who already hold AA or BA degrees at the time they enter college; students who are taking community college classes, but are also enrolled at either K-12 or continuing education classes; students who have not finished high school and are not currently enrolled in K-12 schools; and students with high school degrees earned outside of the United States. We further limit the sample to students between the ages of 18 and 40. Finally, because our main intent is to explore how student performance differs by instructional modes, we limit our sample to courses in which both FtF and online options were offered at the same college in the same term. These restrictions narrow our sample from 440,500 unique students to roughly 217,000 students. Appendix Table A1 traces how the sample composition changes as these limitations are imposed.

Measures and Models

Main independent variable. Our primary variable of interest is an indicator (*Online*) for whether a student took a given course online through either synchronous or asynchronous delivery. For each section of each course offered in each term at each college, we observe the instructional delivery mode. We compare FtF instruction with instruction that took place through either synchronous or asynchronous online delivery modes.

Outcomes. We explore how online course-taking is associated with a series of outcomes. The first is an indicator for whether a student completed the course. Students are considered to have completed courses if they receive a letter grade (A-F), or a pass or no pass designation. Students with incompletes, or who withdraw or are dropped by the instructor from the class, are counted as having not completed the course. Students who withdraw due to military obligations receive a distinct grade notation signifying the reasons for withdrawal, and are excluded from the analysis. Likewise, students who withdraw during the add/drop period—before a course enrollment would appear on their permanent record—are excluded from the analysis.

A second set of analyses captures whether a student completes the course with a passing grade. This outcome variable is coded 1 if students complete the course with an A, B, C, or Pass grade; withdrawals as well as F and D grades are coded as 0. We refer to this as the Pass/A/B/C or the "course passing" outcome. This is perhaps our most policy-relevant outcome, as receipt of an A, B, C, or Pass grade allows students to transfer credits to four-year institutions.[2]

Our final take on the course performance outcome uses an indicator variable for whether students receive an A or B grade. Because the way that future institutions might view pass grades is ambiguous (i.e., whether they would equate a Pass to a C or whether they would view it more akin to an A or B), we exclude students graded on the pass/no pass options in this analysis.[3] We refer to this as the "A/B receipt" outcome.

<u>Controls.</u> Student controls include both time-variant and time-invariant variables. Time-variant controls include a variable that captures age-at-term, the number of units a student enrolls in for in a given term, and the financial aid status of the student. The financial aid status comprises an indicator variable for whether the student receives a Board of Governors tuition waiver. The waiver is needs-based, and virtually all students receiving financial aid receive the waiver as part of their financial aid packages.

Time-invariant controls include a vector of race indicators (Hispanic, Asian, Black, Other; White is omitted), an indicator for whether a student is female, and the type of prior educational credential received at entry into the California Community College system (high school diploma, GED or California High School Proficiency credential). We also create a vector of indicators on the academic goals that students report to the college. Students are coded as having goals to transfer to a four-year college (with or without an AA degree), to pursue an AA

[2] Pass grades may be accepted if the community college's policy states that this is equivalent to receiving a C or better in a course.
[3] Using other outcomes, including failure conditional on course completion and course grade conditional on course completion, gives us similar patterns of results.

degree with no intent to transfer, to further vocational goals, to pursue personal interests, to improve basic skills, or as having unknown goals.

We also include indicators for the course skill level. Courses are coded as basic-skills level (remedial), transferrable to the California State University (CSU) system only, transferrable to the CSU and University of California systems; or non-transferrable but not basic-skills level.

Models

In an ideal world, we would evaluate the causal effect of taking a course online versus face-to-face using a controlled experiment in which we could randomly assign students taking a randomly chosen set of courses to online versus FtF course sections and observe their relative course performance. Such an experiment would provide strong internal as well as external validity of estimates of the effects of online course-taking. However, such an experiment is not feasible in the real world on a wide scale. We therefore use quasi-experimental techniques to build up progressively better-controlled models to explore how online course-taking is associated with student outcomes. A naïve approach would be to simply estimate an OLS regression:

$$(0.1)\; Y_{iscjt} = \alpha + \beta Online_{scjt} + \gamma Course_{scjt} + \delta Student_{it} + \theta_t + \varepsilon_{istcj}$$

where Y represents the outcome of interest for student *i* observed in section *j* of course *c* at college *s* in term *t; Online* indicates whether the student enrolled in an online section, *Course* is a vector of other course characteristics, *Student* is a vector of time-varying and time-invariant student characteristics, θ_t is a vector of term fixed effects that index the academic term and year that a course was offered, and ε_{istcj} is an independently and identically distributed error term.

However, this approach raises serious concerns about bias on two levels. First, we might be concerned that course enrollments might be skewed so that online enrollment was concentrated in courses that were either more or less challenging than the average FtF course. In other words, our estimates might be biased because of sorting in how online courses are offered across different types of classes and among different institutions. To address this concern, we introduce course-by-college fixed effects (θ_{sc}):

$$(0.2)\, Y_{iscjt} = \alpha + \beta Online_{scjt} + \delta Student_{it} + \gamma Course_{scjt} + \theta_t + \theta_{sc} + \varepsilon_{istcj}$$

This approach allows us to compare students taking the same courses in the same schools but through different delivery modes.[4]

We still might be concerned that students who opt into online sections of a course may systematically differ from their peers in FtF sections of the same course. For instance, say students who prefer FtF courses are more engaged with college life in general and that engagement is correlated with performance either positively (e.g., if engagement means students are more motivated to do well) or negatively (e.g. if engagement means that students are distracted by other college activities). These differences across the types of individuals who are prone to enroll in FtF versus online course sections would bias comparisons of the relative performance of online versus FtF students.

To address the likelihood that certain types of individuals might prefer online courses *in general*, we use individual fixed effects θ_i:

$$(0.3)\, Y_{iscjt} = \alpha + \beta Online_{scjt} + \theta_i + \delta Student_{it} + \gamma Course_{scjt} + \theta_s + \theta_k + \theta_t + \varepsilon_{istcj}$$

This method allows us to hold the individual (and therefore their generic "taste" for online courses) constant, and compare an individual's performance in the classes she takes online with her own performance in FtF classes. In our initial models, we follow past literature (Johnson &

[4] Note that course-by-college fixed effects implicitly include within them fixed effects for the college as well as the course, so including this term controls for time-invariant characteristics of courses and colleges. We retain the course vector because transfer status can be time-variant.

Cuellar Mejia, 2014; Xu & Jaggars, 2014) by using college (θ_s) and subject (θ_k) fixed effects to control for college-level and subject-level differences in these specifications.

However, this method still raises a number of concerns. Most obviously, individuals who are observed in both types of classes might be making the decision about when to enroll in online versus FtF courses based on criteria that are correlated with the outcomes we are interested in. For instance, perhaps students are more likely to enroll in FtF classes when they anticipate that the material will be especially challenging and they want the opportunity to ask questions of instructors in person. Alternatively, perhaps students are more likely to enroll in online sections of courses that they anticipate will be difficult, for instance if they believe that they will retain information less well if it is delivered in a lecture that they cannot repeat and review at their convenience. If students make decisions about online versus FtF enrollment with an eye to issues that are likely to be correlated with their performance, our individual fixed effects estimates will still suffer from bias. We explore the extent to which our estimates are likely to suffer from such bias in our results section. We also address these concerns by estimating a final set of fixed effects models that simultaneously estimate both individual and college-course fixed effects:

$$(0.4) \qquad Y_{iscjt} = \alpha + \beta Online_{scjt} + \theta_i + \delta Student_{it} + \gamma Course_{scjt} + \theta_{sc} + \theta_t + \varepsilon_{iscjt}$$

In order to account for the possibility that student outcomes may be correlated within institutions, all models are estimated using robust standard errors clustered at the college level.

Results

Descriptive Results

Table 1 presents descriptive statistics on who takes online courses. Statistics are presented for three groups: the full sample, FtF-only students, and ever-online students. Observations represent unique student counts. Females, Whites, and Asians are all disproportionately likely to be in the ever-online group relative to FtF-only. Ever-online students are less likely to ever enroll in basic courses, and are more likely to state that their primary goal is to transfer to a four-year college than are students who take courses only face-to-face. Ever-online students have higher first-term GPAs and attempt more units in their first term, on average, than FtF-only students. While these statistics suggest that ever-online students may be a better-prepared group on average than FtF-only students, they are more likely to receive need-based aid at some point during the years covered by our data.

Table 2 presents the course characteristics of sections that are taught face-to-face or online. Descriptively, we see that students in online sections have significantly lower completion rates, significantly lower rates of course passing (with an A/B/C or Pass grade) and significantly lower rates of A or B receipt. Online courses are slightly less likely to be basic skills status, and more likely to confer credits that are transferable to four-year colleges. The share of classes offered during the summer session is over twice as high for online courses as for FtF courses. The distribution of courses across subject areas differs for the two instructional modes as well; for instance, business and management courses represent only about 5% of course enrollments in FtF sections, but over 10% of online enrollments. Conversely, subjects like math and humanities are under-represented in online enrollments relative to FtF enrollments.

Main results

To test how online course-taking is associated with student outcomes, we build up a series of models using progressively stronger designs. Table 3 presents these results. Each cell represents the coefficient of the *Online* indicator variable in a model estimating the dependent variable specified in the row label. To get a sense of raw comparisons, Column 1 presents the bivariate relationship between online course enrollment and course completion, course failure conditional on completion, and course grade conditional on completion. The bivariate results confirm the comparisons presented in Table 2; students are significantly less likely to complete courses when they are taken online and less likely to achieve a successful (pass/A/B/C) result. The likelihood of receiving an A or B (vs. withdrawing or receiving a C, D or F), however, is not significantly different between the two types of class once we correct the standard errors for within-school clustering.

Column 2 adds controls for course characteristics and fixed effects for the term that a course is taken. The results for course completion and course passing remain very similar to the bivariate specification presented in Column 1, although the magnitudes of the coefficients increase slightly. The coefficient for A/B receipt also grows in magnitude and becomes significantly and negatively associated with course grade in this specification. We obtain similar results in Column 3, which adds time-variant and time-invariant individual controls. The A/B receipt coefficient nearly doubles in magnitude, but the basic pattern of results is the same: Online course-taking is associated with significantly worse results across all three outcomes.

Since our modest course controls may not fully remove the confounding influence of differences in characteristics of the types of courses that disproportionately enroll students online, our next set of analyses incorporate course-by-college fixed effects. The substantive results, presented in Panel A of Table 4 are very similar to those presented in Table 3, although the magnitudes of the coefficient grow slightly. The results suggest that online course enrollment is associated with a 6.8 percentage point decrease in the likelihood that a student will complete a course, a 10.9 percentage point decrease in the likelihood that a student will pass a course, and a 7.5 percentage point reduction in the likelihood that a student will pass with an A or B. These results are all statistically significant.

Because the results presented in Table 4 include college-course fixed effects, they should control for the possibility that the types of courses that disproportionately enroll students in online sections are systematically more or less difficult than courses that disproportionately enroll students face-to-face. However, they may still suffer from bias if the types of students who have a stronger natural "taste" for online courses are also more (or less) likely to perform well in college courses.[5] We address these concerns in two ways.

First, we explore the extent to which student sorting may be biasing our estimates. We explore student performance in courses in the fall term of 2008 among students who enrolled only in FtF courses in that term, and include an indicator for whether a student is observed in an online course *in future terms.* This indicator should not be associated with course performance in the current term unless there is selection into online course sections on unobservable dimensions not accounted for by the student and course-college controls we currently include.[6] We limit the sample in these models to students who persist through at least two more terms (Spring and Fall 2009) to ensure that the *Future Online* indicator is not picking up a differential level of persistence among students, and the *Future Online* indicator accordingly applies only to those two terms (rather than summer terms, the 2010-11 school-year, etc.). At the same time, we broaden the range of courses to include the full set of face-to-face courses, rather than only courses offered in both formats.

Our results provide little evidence of sorting into online courses in a way that explain away our estimates (Table 4, Panel B). Future online course-taking is not related to course

[5] There is also evidence that student selection into online courses is related to issues such as student convenience (e.g. work schedules, child care, and proximity to campus) (California Community College Chancellor's Office, 2011; Jaggars, 2013; Noel-Levitz, 2011).
[6] Conceptually, this is similar to the falsification tests that Rothstein (2010) conducts to explore whether student sorting into classrooms biases estimates of teacher value-added measures.

completion among FtF-only students taking courses in Fall 2008, but is positively predictive of the other two outcomes. Note, however, that these associations are in the opposite directions of the main results, suggesting that if anything, sorting into online courses is positively associated with skill. The magnitudes of these estimates are very modest. Overall, this test suggests that our course-by-college fixed effects results presented in Table 4, Panel A are conservative estimates of the negative association between online course-taking and course performances.

The second way that we address concerns that individual sorting into online courses may contaminate our results is to estimate models using individual fixed effects. This allows us to compare a student's performance in online courses with her own performance in FtF courses.[7] For our initial pass using individual fixed effects, we drop the course-by-college terms and substitute college and subject fixed effects.

The pattern of results using individual fixed effects estimation (Table 5), are strikingly similar to those shown in Table 3 and Table 4. However, the magnitudes of the coefficients grow slightly under this specification. The results suggest that students are roughly 8.4 percentage points less likely to complete, and 14.5 percentage points less likely to pass, the online courses that they enroll in than to complete the courses they take through FtF instruction. They are 11.0 percentage points less likely to receive A or B grades in online courses than in FtF courses.

Because we are still concerned that the factors that impel students to enroll in FtF versus online courses may bias our estimates, we explore whether we can predict characteristics of a given course based on whether we know that a student has opted for online versus FtF enrollment. In these specifications, course characteristics are entered one-by-one as dependent

[7] The coefficients on the online indicator in these models are therefore identified off of students who are observed in both instructional modes, although students observed in only one mode are included to improve the precision of the estimates of the other coefficients.

variables. We retain our main course characteristic controls (basic level, transfer eligibility, and subject fixed effects). While controlling for those measures in our main specifications should allow us to adjust somewhat for possibility that classes that students opt into for online instruction are more or less “difficult” than the FtF classes that they enroll in, we explore four new measures that may be correlated with both students’ decisions to select into online sections and the course performance.

Our first three measures capture the average student performance in the courses students enroll in. Because we want to eliminate the influence of the student’s own performance, or of any shocks that may have affected both the student’s performance and the average class performance, we use lagged measures of average student performance for the entire year prior in FtF sections of the course. We limit our outcome measures to average performance in FtF sections to eliminate the possibility that different grading practices or general student success in online courses will affect average grades. This measure should provide a gauge of how successful students could expect to be in a FtF section of the course; if the online classes that students opt into are systematically more or less “difficult” than the FtF classes that they enroll in, that would raise the possibility of bias in our individual fixed effects estimates. Table 5, Panel B provides no evidence of differential selection on these dimensions (Columns 1-3).

As a second gauge, we generated a measure for whether a student’s enrollment in a given course was an effort to retake a course that they had previously performed poorly in or failed to complete. These results (Column 4) suggest that there is little relationship between online course-taking and the likelihood that a student is retaking a given course. These analyses provide no evidence that students are systematically deciding to take online versus FtF courses in a way that would bias our results.

One might be concerned that even if students do not differentially select into online course formats based on course characteristics, there may be term-varying individual factors that both influence students' propensity to take online courses and their performance. For instance, perhaps students sign up for online courses when they anticipate particularly heavy work schedules, which also crowd out study time and impact students' course performance. If online enrollment is just a proxy for students' being particularly busy in a given term, we might also expect to see students' performance in face-to-face courses drop in terms where they are enrolled in online courses. In additional tests (available on request), however, we find that students' performance in face-to-face courses is essentially unrelated to an indicator for whether they are taking any online courses in the contemporaneous term (coefficients on the indicator are non-significant for all three outcomes, and range from -0.001 to 0.002).

Finally, in our most robust set of fixed effects estimates (Table 6), we included a set of college-course and individual fixed effects simultaneously (Cornelissen, 2008). This allows us to simultaneously account for course-invariant unobservable student factors and student-invariant unobservable course-level factors that may each predict students' course performance. These coefficients are very similar to those estimated using the individual fixed effects in Table 5, Panel A. Taken together, these estimates give a strikingly stable picture of weaker student performance in online courses than in face-to-face formats.

Faculty Characteristics

Our results thus far suggest that neither student sorting across classes nor choices by students to take particularly challenging courses online account for the negative relationship between online enrollment and student performance. We next consider whether differences in faculty characteristics across the two types of classes play a role. We look at four main types of faculty characteristics: the contract status of the faculty member (temporary, tenure-track non-tenured ("pre-tenure"), or tenured); years of experience (0-2 years, 3-5 years, 6-10 years, 11 or more years); whether the faculty is teaching any courses as an overload in a given term; and whether the course is team-taught.[8]

We first explored whether these differences might be expected to matter for student achievement (Table 7, Panel A). These models include a vector of instructor measures as predictor variables, without the inclusion of online status, in a model otherwise like Equation 0.2. Each cell reports the coefficient on the predictor variable identified in the column header on the dependent variable identified in the row label. We find that the contract status and experience variables are significantly related to student outcomes. Pre-tenure and temporary instructors are associated with better student performance across all three outcomes than are tenured professors (though the coefficient is non-significant for the A/B outcome for pre-tenure instructors), and more experience is negatively related to course completion, course passing, and A/B receipt. We found no relationship between instructor overload and multiple instructors on student outcomes; these results are therefore omitted from the tables for brevity.

The bottom (bolded) rows of Table 7, Panel A give the coefficients and standard errors on the *Online* predictor for models where Equation 0.2 was estimated using each faculty characteristics as a dependent variable. That is, the bolded rows indicate whether being in an online section predicts being exposed to a faculty with the characteristics indicated in the column header. We find that the contract status and experience variables are related to online status: Online students are significantly more (less) likely to have tenured (temporary) instructors and

[8] In practice, classes with multiple instructors comprise only 1% of classes. Instructor variables (e.g., years of experience) for these classes reflect the status of the instructor responsible for a greater share of the course (based on reported percent effort), or the more senior professor.

significantly more (less) likely to have teachers with more than 11 (fewer than 6) years of experience. Taken together, these results are suggestive that online students may perform less well than their peers partly because they are exposed to a group of faculty associated with poorer student performance on the metrics we explore.[9]

To see whether the differences in faculty in online versus FtF sections explained any of the online-FtF performance gap, we re-ran Equation 0.2 including the faculty characteristics as controls (Table 7 Panel B). The *Online* coefficients diminish, but the change is small. For instance, the *Online* coefficient for the school-course fixed effects specification (replicated in Column 1) for the Pass/A/B/C outcome declines in magnitude from -0.109 to -0.104 when faculty characteristics are included in Column 2, but the new (Column 2) point estimates are well within the confidence interval of the original (Column 1) estimates. We see similar patterns if we introduce faculty controls into the individual fixed effects specifications (not shown).

Our measures of teacher characteristics are fairly rough and do not preclude the possibility that independent of observable teacher characteristics, instructors who are either tougher graders or less effective teachers could disproportionately opt into online teaching. To explore whether our results were robust to this possibility, we ran a final set of models using instructor fixed effects. As with the individual fixed effect specifications in Table 5, subject matter and college fixed effects were included in lieu of school-course fixed effects. These models identify off of instructors who teach in both online and FtF courses. We find that within instructors, students perform worse in instructors' online sessions than in their FtF courses (Table 7, Panel B, Column 3), although the magnitude of the coefficients is slightly smaller in

[9] Note that since we use some subjective measures of performance, it is hard to sort out whether non-tenured, less experienced instructors are easier graders or promote better performance.

these specifications than in Column 1. Taken together, these results suggest that little of the online-FtF performance gap can be explained by exposure to systematically tougher or less effective faculty teaching in the online setting.

Heterogeneity by Course Characteristics.

We next explored whether the relationship between online course-taking and student performance outcomes varied by course characteristics. Table 8 represents eight sets of mutually exclusive factors by which we categorize courses: 1) Whether the class offers credits transferable to the four-year California State or University of California systems. 2) Course difficulty, proxied by the year-prior pass/A/B/C rates in FtF sections of the course. Classes with a less-than (at least) 66% passing are classified as having a low (high) pass rate. 3) Course length (semester, quarter, intersession). 4) Course timing (academic year versus summer). Intersession courses are dropped from these analyses. 5) Instructor contract type (temporary, tenured, pre-tenure). 6) Instructor experience (at least 6 years, 5 years or less). 7) Share of students in online classes. This variable captures the share of students in our sample that take the class online in a given school-term. 8)Academic subject area. We include subjects with over 300 school-course clusters.

Interaction terms (*Online* interacted with a vector of *CourseCharacteristic* measures) were added to the college-course fixed effects models. Each cell represents the difference between student performance on the pass/A/B/C outcome in online and FtF courses for the group identified in the row label. That is, each cell represents the linear combination of the *Online* main effect and the relevant *Online*CourseCharacteristic* coefficients for the non-omitted groups. The column to the right of the estimates indicates which groups had online "effects" significantly different at p<.05 from the group represented in the referent row. Group numbers within each comparison set are given in the row labels. The right-most column shows the number of unique school-course clusters classified in the group identified in the row labels.

We highlight two facets of the results here. First, we see the same pattern of results across all course types: In all cases, online course enrollment is significantly and negatively associated with the pass/A/B/C outcome. Analyses using our other outcome measures show similar results.

Second, we see some types of courses where the online-FtF gaps are systematically larger. For instance, the gap is nearly three percentage points larger in non-transfer-eligible classes than in classes conferring transferable credits. We initially posited that the performance gaps may be exaggerated in classes with generally lower course passing rates, as these classes may be especially difficult, but we found the opposite was true. Classes where students were more successful (in FtF sections) had larger performance gaps than those with low passing rates.

Courses that took place outside of the regular academic calendar likewise were associated with especially large online-FtF performance gaps. The online-FtF performance gap was roughly five percentage points higher for intersession courses than for classes offered in a typical semester or quarter-length format, and the performance gap was nearly seven percentage points larger (over two-thirds higher) in summer than during the traditional academic year.

The share of a student's cohort mates who were in online (vs. FtF) sections of a course also moderated the online-FtF performance gap. The performance gap was significantly higher when a relatively small share of students (<15%) were in online sections than when a high share (greater than or equal to 40%) were enrolled through online sections. This difference remained when we included *OnlineXSubject* interactions to check whether the result stemmed from differences in enrollment across subject types. These results suggest that online students benefit from having a critical mass of peers taking the class in the same format.

Finally, online-FtF performance gaps were particularly pronounced in certain subjects. Math and humanities (which includes English Language Arts classes) saw performance gaps that were about two to three percentage points (20-30%) higher than gaps observed in other classes.

Some of the factors that we thought might moderate the gap were irrelevant: there are no differences in the size of the gap across instructor contract types or instructor experience.

Heterogeneity by Student Characteristics.

Finally, we explored heterogeneity in outcomes by student characteristics using the individual fixed effects models. The *Online* variable was interacted with indicators indexing students' positions in several categories: 1) basic skills class enrollment (any basic skills classes during our study period versus no basic skills classes); 2) Student first-term academic performance (student passed all FtF classes with A/B/C/Pass vs. at least one withdrawal/NP/F/D. Students' first-term observations were excluded from these analyses); 3) Stated academic goal (transfer to a four-year institution versus any other goal); 4) Student course load (more than full-time, full-time, less-than-full time)[10]; 5) Student age at entry (traditional college-aged, e.g., 18-22 vs. older [23 or older]); 6) Student financial aid use (Ever vs. Never); 7) Student sex (female versus male); 8) Student racial/ethnic group (Hispanic, White, Black, Asian, or Other). Results presented in Table 9 give the online-vs.-FtF difference for the group indicated in the row label, i.e., each cell represents the main effect of *Online* on the Pass/A/B/C outcome for the omitted group plus the *OnlineXGroup* interaction term for the relevant group. The column to the right of the estimates indicates the groups for which the *Online* "effect" on the pass/A/B/C outcome is

[10] Credits taken for full-time status varies based on whether schools are on semester or quarter systems. The full-time load at semester (quarter) system schools is 12 (18) units.

significantly different than the referent group. Group numbers are designated in the row labels. The final column gives the number of students in the category designated in the row label.

Again, as for the heterogeneity by course characteristics, we find that no matter how we split the sample, the coefficients on the *Online* predictor for all outcomes are significant and negative. The stability of these results across different types of students is striking.

However, we also see some groups for which performance gaps are wider. For instance, students who were successful academically in their first term had smaller online-FtF gaps than did their peers who failed or withdrew from at least one class (12.7 percentage points vs. 14.3). Transfer-oriented students also had significantly smaller online-FtF performance gaps than did their non-transfer-oriented peers. Students taking a more-than-full-time course load had the smallest online-FtF performance gap (12.2 percentage points), significantly smaller than either full-time students (14.0 percentage point gap) or part-time students (15.2 percentage points).

Unlike past studies (Xu & Jaggars, 2014; Johnson & Mejia Cuellar, 2014), in our sample females have a larger online-FtF performance gap than males. Notably, however, this is outcome-dependent: Males have a larger online-FtF performance penalty when course completion is used as the outcome, suggesting that females are particularly prone to increased rates of course failure/non-passing conditional on course completion in online courses.

We find that Asian students have smaller online-FtF performance gaps than all other groups; the negative coefficient for Asian students (7.5 percentage points) is less than half as large as that for Latino (15.3 percentage points) or Black (16.5 percentage points) students.

We find no differences in the size of the coefficients based on financial aid receipt, age at entry, or basic-skills class enrollment history.

Discussion

Our results suggest that student performance in online courses is generally weaker than in FtF classes. These results hold whether we use college-course fixed effects, individual fixed effects, or faculty fixed effects. Our results are consistent for students with different characteristics, and for courses with different characteristics. The consistency of these results across different methods of specification and for different groups adds credence to our findings. Our results are close in magnitude to results from similar studies conducted in multiple states (Xu & Jaggars, 2011; Xu & Jaggars, 2013; Johnson & Cuellar Mejia, 2014). In addition, the coefficients' stability and the fact that the coefficients become more negative as we add controls suggests that the degree of selection on unobservables (Altonji, Elder, Taber, 2005; Oster, 2013) would have to be substantial and in the opposite direction from selection on observables to invalidate the fixed-effect results.

The consistency of our results is important from a policy perspective. Policymakers in California and other states are interested in exploring whether online courses can be used to expand student and improve outcomes. The results suggest that there may be costs to this strategy, although formal cost-benefit analyses should explore whether the greater likelihood of course non-completion or failure offsets the possible cost savings associated with online courses.

In addition, our results on how the online course penalty varies across course types should help college administrators plan the instances in which online courses may be least costly to students taking them. For instance, students who relocate for a summer job and want to take a summer class online through their home institution may be advised to consider whether there is a campus closer to their summer location where they could take FtF sections instead. Colleges may also consider limiting how many online sections are offered during the summer. Our finding that the online-FtF penalty is more muted when a larger share of students are in online sections also deserves more exploration to determine what factors (e.g., whether a critical mass is associated with greater peer or departmental support for online students) are responsible for this result.

Our results also have implications for student support in online classes. Faculty members teaching online should be aware of the performance penalty associated with taking courses online and consider implementing course policies and practices that would allow them to detect student disengagement in the absence of the physical cues that FtF instructors can rely on. Students should be made aware that success rates are systematically lower in online than in FtF sections so that they can make informed enrollment decisions, and should be introduced to study strategies and time management strategies that promote success in online formats.

The present study has several limitations that should be kept in mind. Its generalizability may be limited. If, for instance, college systems in other states have more (or less) well-developed online course delivery systems, the results presented here might not generalize well. If the current crop of courses in which online sections are offered are either better or worse suited to online delivery than courses that have not yet adopted online sections, the results may not generalize to different types of courses. Likewise, the results might not generalize cleanly to students attending other types of colleges (e.g., four-year institutions, for-profit schools) that have different organizational and instructional cultures. That said, our tests for heterogeneity of effects for different groups of students somewhat eases our concerns about external validity.

Finally, further research should seek to establish even stronger causal estimates of online course-taking. While our tests suggest that selection likely plays a limited role in explaining the negative relationship between online enrollment and course performance, future randomized trials under different course conditions will be important to more firmly establish the causal link between online course-taking and student outcomes.

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Figure 1. Expansion of student enrollments in online courses, fall 2003-2011

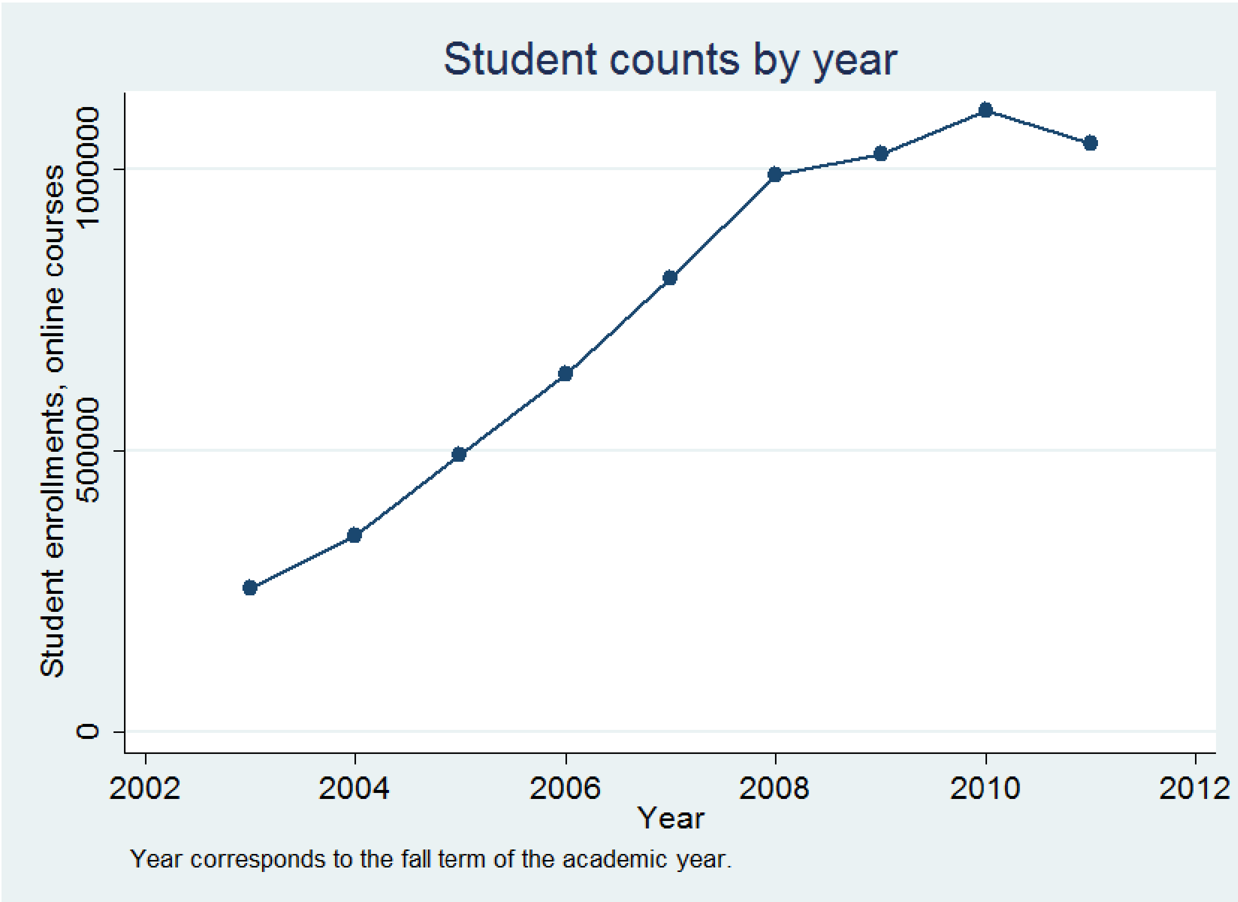

Table 1. Student Characteristics, Students First Enrolled in 2008-09 School-year

	(1) Full Sample mean/sd	(2) FtF Only mean/sd	(3) Ever Online mean/sd
Pre-college Individual Characteristics			
Age at first CCC term	20.31	20.02	20.73
	(4.19)	(3.85)	(4.61)
Female	0.52	0.48	0.57
	(0.50)	(0.50)	(0.50)
Hispanic	0.36	0.41	0.30
	(0.48)	(0.49)	(0.46)
White	0.31	0.28	0.36
	(0.46)	(0.45)	(0.48)
Asian	0.08	0.08	0.10
	(0.28)	(0.26)	(0.30)
Black	0.10	0.10	0.09
	(0.29)	(0.30)	(0.29)
Other race	0.15	0.14	0.15
	(0.35)	(0.35)	(0.36)
High school diploma	0.93	0.93	0.92
	(0.26)	(0.26)	(0.26)
GED	0.06	0.06	0.06
In-college Individual Characteristics			
Ever takes basic courses	0.42	0.44	0.39
	(0.49)	(0.50)	(0.49)
Ever receives financial aid	0.58	0.56	0.60
	(0.49)	(0.50)	(0.49)
First-term GPA	2.19	2.04	2.40
	(1.28)	(1.30)	(1.22)
Units attempted first term	9.24	9.05	9.51
	(4.24)	(4.14)	(4.37)
Modal goal: Transfer	0.54	0.52	0.56
	(0.50)	(0.50)	(0.50)
Modal goal: AA no transfer	0.06	0.06	0.06
	(0.23)	(0.23)	(0.23)
Modal goal: Vocational	0.08	0.08	0.07
	(0.27)	(0.28)	(0.26)
Modal goal: Unknown	0.28	0.29	0.27
	(0.45)	(0.45)	(0.44)
Modal goal: Personal interest	0.04	0.04	0.04
	(0.20)	(0.20)	(0.19)
Modal goal: Basic skills	0.01	0.01	0.01
	(0.09)	(0.10)	(0.09)
Unique students	**217,194**	**128,851**	**88,343**

Means (SD) given.

Table 2. Course Characteristics, Students first enrolled in 2008-09

	(1) All Courses mean/sd	(2) FtF Course Sections mean/sd	(3) Online Course Sections mean/sd
Course Outcomes for Sample			
Completion Rate (%)	83.63	84.58	78.99
	(37.00)	(36.12)	(40.74)
Pass/A/B/C Rate (%)	61.41	62.52	55.98
	(48.68)	(48.41)	(49.64)
A/B Receipt Rate (%)	42.20	42.37	41.38
	(49.39)	(49.41)	(49.25)
Share of Courses that Are:			
Basic Skills Status(%)	4.96	5.33	3.25
	(21.71)	(22.45)	(17.72)
Transferrable to UC or CSU Systems (%)	73.39	73.24	74.10
	(44.19)	(44.27)	(43.81)
Transferrable Only to CSU System (%)	8.15	6.86	14.16
	(27.36)	(25.28)	(34.87)
Share of Courses Offered in:			
Fall Term (%)	47.91	48.93	43.16
	(49.96)	(49.99)	(49.53)
Spring Term (%)	45.51	45.37	46.13
	(49.80)	(49.79)	(49.85)
Winter Term (%)	0.59	0.60	0.52
	(7.65)	(7.75)	(7.19)
Summer Term (%)	4.52	3.73	8.22
	(20.78)	(18.95)	(27.47)
Share of Courses Offered as:			
Semester Class (%)	96.61	96.68	96.27
	(18.09)	(17.90)	(18.95)
Quarter Class (%)	1.92	1.95	1.76
	(13.71)	(13.83)	(13.16)
Intersession Class (%)	1.47	1.37	1.97
	(12.04)	(11.60)	(13.89)
Share of Courses in Different Subject Areas (%):			
Agriculture/Natural Resources	0.04	0.03	0.09
	(1.91)	(1.60)	(2.96)
Architecture/Environmental Design	0.00	0.00	0.01
	(0.55)	(0.38)	(1.02)
Environmental Science/Tech	0.07	0.05	0.14
	(2.62)	(2.33)	(3.69)
Biological Sciences	1.47	1.44	1.60
	(12.04)	(11.93)	(12.53)
Business/Management	6.36	5.51	10.34

	(24.41)	(22.82)	(30.45)
Media/Communications	1.14	0.95	2.05
	(10.63)	(9.70)	(14.16)
Information Technology	3.61	2.82	7.29
	(18.65)	(16.55)	(26.00)
Education	4.39	4.17	5.44
	(20.50)	(19.99)	(22.67)
Engineering/Industrial Technology	0.08	0.06	0.15
	(2.76)	(2.43)	(3.93)
Foreign Languages	0.77	0.70	1.10
	(8.73)	(8.32)	(10.43)
Health	0.42	0.32	0.91
	(6.49)	(5.62)	(9.51)
Family/Consumer Sciences	4.23	3.93	5.60
	(20.12)	(19.44)	(22.99)
Law	0.10	0.07	0.23
	(3.12)	(2.62)	(4.79)
Humanities	22.53	23.96	15.84
	(41.78)	(42.68)	(36.51)
Library Science	0.24	0.14	0.72
	(4.90)	(3.71)	(8.47)
Mathematics	16.49	17.94	9.71
	(37.11)	(38.37)	(29.60)
Military Science	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Physical Science	1.41	1.32	1.83
	(11.78)	(11.39)	(13.42)
Psychology	8.49	8.74	7.33
	(27.88)	(28.25)	(26.07)
Public/Protective Services	1.67	1.50	2.46
	(12.81)	(12.15)	(15.49)
Social Sciences	23.43	23.36	23.75
	(42.35)	(42.31)	(42.55)
Commercial Services	0.01	0.01	0.02
	(0.97)	(0.80)	(1.53)
Interdisciplinary	3.06	2.98	3.39
	(17.21)	(17.02)	(18.10)
Course Enrollments	987,868	813,619	174,249

Means (SD) given. Observations include course enrollments for cohort entering in 2008-09. Winter terms offered only under the quarter system

Table 3. Association between Online Course-taking and Student Outcomes: Multivariate Regression Models

Outcome	(1) b/se	(2) b/se	(3) b/se
Complete	-0.056***	-0.061***	-0.061***
	(0.004)	(0.003)	(0.003)
Pass ABC	-0.065***	-0.085***	-0.101***
	(0.006)	(0.005)	(0.005)
A or B	-0.010	-0.031***	-0.060***
	(0.006)	(0.006)	(0.006)
Term FE		Y	Y
Course Controls		Y	Y
Individual Controls			Y
Colleges	109	109	109
College-Courses	6,200	6,200	6,200
Students	213,568	213,568	213,568
Student-Course-Terms	953,933	953,933	953,933

Coefficient (within-college correlation robust SE). Significance: *0.10 **0.05 ***0.01. Sample limited to first-time students entering in the 2008-09 academic year observed in college-courses offered in both formats in the same term. Missing variable dummies included. Student-course-term numbers are for Complete outcome variable. The pass/A/B/C and A/B models respectively include 953,933 and 933,125 student-course-term observations. R-squared statistics for Column 3 are .016, .05, and .056 for the Complete, Pass/A/B/C, and A/B outcomes respectively.

Table 4. Association between Future Online Course-taking and Student Outcomes: School-course Fixed Effects Models. Future terms include Spring 2009 and Fall 2009

Panel A. Main Results

	(1) Complete b/se	(2) Pass/A/B/C b/se	(3) A or B b/se
Online	-0.068***	-0.109***	-0.075***
	(0.003)	(0.005)	(0.005)
College-Course FE	Y	Y	Y
Colleges	109	109	109
College-Courses	6,200	6,200	6,168
Students	213,568	213,568	211,724
Student-Course-Terms	953,933	953,933	933,125
R-squared	0.048	0.088	0.105

Panel B. Falsification Test

	(1) Complete b/se	(2) Pass/A/B/C b/se	(3) A or B b/se
Takes Online in Future	-0.000	0.013***	0.015***
(through Fall '09)	(0.002)	(0.004)	(0.004)
College-Course FE	Y	Y	Y
Colleges	105	105	105
College-Courses	19,157	19,157	18,379
Students	78,313	78,313	77,017
Student-Course-Terms	234,021	234,021	216,877
R-squared	0.137	0.170	0.206

Coefficient (within-college correlation robust SE). Significance: *0.10 **0.05 ***0.01. Sample limited to first-time students entering in the 2008-09 academic year. Panel A limited to students observed in college-courses offered in both formats in the same term. Panel B includes students who are observed only in face-to-face courses in Fall 2008, and who persist through Fall 2009, but includes all face-to-face courses (whether offered in both formats or not). Term fixed-effects, individual controls, course controls, and missing variable dummies included.

Table 5. Association between Online Course-taking and Student Outcomes: Individual Fixed Effect

Panel A. Main Results

	(1) Complete b/se	(2) Pass/A/B/C b/se	(3) A or B b/se
Online course	-0.084***	-0.145***	-0.110***
	(0.004)	(0.006)	(0.006)
Individual FE	Y	Y	Y
Students	213,568	213,568	211,724
Student-Course-Terms	953,933	953,933	933,125
R-squared	0.379	0.475	0.473

Panel B. Test for Selection on Course Characteristics

	(1) Lagged FtF Completion Rate b/se	(2) Lagged FtF Rate: Pass/A/B/C b/se	(3) Lagged FtF Rate: A/B b/se	(4) Retake Effort b/se
Online course	0.001	-0.002	0.001	0.002
	(0.001)	(0.002)	(0.003)	(0.003)
Individual FE	Y	Y	Y	Y
Students	205,881	205,881	205,880	213,568
Student-Course-Terms	830,468	830,468	830,445	953,933

Coefficient (within-college correlation robust SE). Significance: *0.10 **0.05 ***0.01. Sample limited to first-time students entering in the 2008-09 academic year observed in college-courses offered in both formats in the same term. Term fixed effects, school fixed effects, subject fixed effects, individual controls, course controls, and missing variable dummies included.

Table 6. Association between Online Course-taking and Student Outcomes: School-Course and Individual Fixed Effects Included Simultaneously

	(1) Complete b/se	(2) Pass/A/B/C b/se	(3) A or B b/se
Online course	-0.089***	-0.152***	-0.120***
	(0.002)	(0.002)	(0.002)
College-Course FE	Y	Y	Y
Individual FE	Y	Y	Y
Colleges	109	109	109
College-Courses	6,200	6,200	6,168
Students	213,568	213,568	211,724
Student-Course-Terms	953,933	953,933	933,125

Coefficient (within-college correlation robust SE). Significance: *0.10 **0.05 ***0.01. Sample limited to first-time students entering in the 2008-09 academic year observed in college-courses offered in both formats in the same term. Term fixed effects, individual controls, course controls, and missing variable dummies included.

Table 7 . Association between faculty characteristics and student outcomes

Panel A. Relationship between Faculty Characteristics and Student Outcomes.

	(1)	(2)	(3)	(4)	(5)
	Temporary Instructor	Pre-Tenure Instructor	0-2 Years Exper	3-5 Years Exper	6-10 Years Exper
Outcome	b/se	b/se	b/se	b/se	b/se
Complete	0.023***	0.018***	0.014***	0.010***	0.007***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Pass/A/B/C	0.036***	0.012***	0.009**	0.009**	0.008*
	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)
A or B	0.032***	0.009	0.024***	0.024***	0.018***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Coefficient on *Online*, var. listed in column header is DV	**-0.161*** (0.014)**	**-0.008 (0.007)**	**-0.056*** (0.005)**	**-0.028*** (0.006)**	**0.012 (0.009)**

Panel B. Association between online course-taking and outcomes with faculty characteristic controlled

	(1)	(2)	(3)
	School-Course FE Baseline	School-Course FE w/ Faculty Controls	Faculty FE
Outcome	b/se	b/se	b/se
Complete	-0.068***	-0.065***	-0.062***
	(0.003)	(0.004)	(0.003)
Pass/A/B/C	-0.109***	-0.104***	-0.089***
	(0.005)	(0.005)	(0.005)
A or B	-0.075***	-0.069***	-0.059***
	(0.005)	(0.005)	(0.005)
College-Course FE	Y	Y	
Instructor Controls		Y	Y
Faculty FE			Y
School-Courses	6,200	6,200	6,200
Instructors	23,556	23,556	23,556
Student-Course-Terms	953,933	953,933	936,681

Coefficient (within-college correlation robust SE). Significance: *0.10 **0.05 ***0.01. Sample limited to first-time students entering in the 2008-09 academic year observed in college-courses offered in both formats in the same term. All models include term, college, and subject fixed effects; individual and course controls; and missing variable dummies included. Student-course-terms are for Completion and Pass/A/B/C outcomes. N for A/B outcome is 933,125(916,185 in faculty fixed effect models). Two other variables tested, exposure to team-taught/ multiple-instructor courses, and whether the course instructor was teaching an overload that term, were not significantly related to student outcomes.

Table 8. Association between online course-taking and pass/A/B/C: Heterogeneity by course characteristics.

	Pass/ A/B/C b/se	Sig. Diff. from Groups	School-Courses in Group
Credits Transfer-Eligible			
Transfer-eligible (Grp 1)	-0.101*** (0.005)	2	5,462
Non-transferrable (Grp 2)	-0.130*** (0.010)	1	860
Lagged FtF Course Pass/A/B/C rate			
Low rate (<66%) (Grp 1)	-0.093*** (0.005)	2	2,982
High rate (>=66%) (Grp 2)	-0.111*** (0.006)	1	5,606
Course Length			
Semester-length (Grp 1)	-0.104*** (0.005)	3	6,014
Quarter-length (Grp 2)	-0.090*** (0.011)	3	183
Intersession (Grp 3)	-0.153*** (0.021)	1,2	256
Course Timing			
Academic year (Grp 1)	-0.098*** (0.005)	2	6,146
Summer term (Grp 2)	-0.169*** (0.010)	1	1,504
Instructor Contract Type			
Temporary (Grp 1)	-0.107*** (0.006)		4,973
Tenured (Grp 2)	-0.104*** (0.006)		4,832
Pre-Tenure (Grp 3)	-0.094*** (0.008)		2,497
Instructor Experience			
6 years plus (Grp 1)	-0.105*** (0.005)		5,733
5 years or fewer (Grp 2)	-0.103*** (0.006)		4,218
Share of Students In Online Sections			
Low (<15%) (Grp 1)	-0.119*** (0.005)	2,3	3,461
Mid-range (15-40%) (Grp 2)	-0.106*** (0.006)	1,3	4,002
High (>=40%) (Grp 3)	-0.087*** (0.006)	1,2	4,154
Subject			
Social Sciences (Grp 1)	-0.093*** (0.008)	3,5	1,093
Bus & Mgmt (Grp 2)	-0.097*** (0.009)	3,5	1,078
Humanities (Grp 3)	-0.122*** (0.007)	1,2,4,6	771
Inf. Tech (Grp 4)	-0.088*** (0.012)	3,5	602
Math (Grp 5)	-0.133*** (0.011)	1,2,46	464
Fam/Consumer Sci (Grp 6)	-0.092*** (0.013)	3,5	377

Cells represent effect of online on pass/A/B/C outcome for the group indicated in the row label (main effect + relevant interaction term). Robust standard errors clustered at school level. Significance: *0.10 **0.05 ***0.01. All models include individual, course and instructor controls; and term and school-course fixed effects. Column 2 indicates groups from which the group represented in the row label has a significantly different Online coefficient. Comparisons group numbers designated in row labels. Course Timing comparisons exclude intersession. Lagged FtF specifications include low lagged FtF classification dummies.

Table 9. Association between online course-taking and pass/A/B/C: Heterogeneity by individual characteristics

	(1) Pass/ A/B/C b/se	(2) Sig. Diff. from Groups	(3) Students in Group
Basic Skills Class Enrollment			
Any (Grp 1)	-0.133***		89,971
	(0.007)		
None (Grp 2)	-0.145***		123,597
	(0.006)		
First-term FtF Academic Performance			
Any non-passed (Grp 1)	-0.143***	2	114,914
	(0.006)		
All passed (Grp 2)	-0.127***	1	85,852
	(0.006)		
Academic Goal			
Transfer (Grp 1)	-0.134***	2	114,504
	(0.006)		
Not Transfer (Grp 2)	-0.147***	1	99,064
	(0.006)		
Student Course Load			
Less than full-time (Grp 1)	-0.152***	2,3	176,267
	(0.005)		
Full-time (Grp 2)	-0.140***	1,3	64,361
	(0.008)		
More than full-time (Grp 3)	-0.122***	1,2	93,081
	(0.007)		
Age at First Term			
Age 18-22 (Grp 1)	-0.140***		178,642
	(0.006)		
Age 23 plus (Grp 2)	-0.135***		34,926
	(0.008)		

	(1) Pass/ A/B/C b/se	(2) Sig. Diff. from Groups	(3) Students in Group
Financial Aid Use			
Ever (Grp 1)	-0.141***		123,815
	(0.006)		
Never (Grp 2)	-0.137***		89,753
	(0.006)		
Student Sex			
Female (Grp 1)	-0.144***	2	109,308
	(0.006)		
Male (Grp 2)	-0.134***	1	102,784
	(0.006)		
Student Race/Ethnicity			
Hispanic (Grp 1)	-0.153***	2,4	77,535
	(0.007)		
White (Grp 2)	-0.141***	1,3,4	66,373
	(0.006)		
Black (Grp 3)	-0.165***	2,4,5	20,081
	(0.009)		
Asian (Grp 4)	-0.075***	1,2,3,5	18,201
	(0.009)		
Other Race (Grp 5)	-0.142***	3,4	31,378
	(0.007)		

Each cell represents effect of online on pass/A/B/C outcome for the group indicated in the row label (main effect + relevant interaction term). Robust standard errors clustered at school level. Significance: *0.10 **0.05 ***0.01. All models include individual and course controls, and term, college, subject, and individual fixed effects. Comparisons group numbers designated in row labels. N=953,933 student-course-terms. First-time FTF academic performance specifications exclude first-term observations.

Appendix A

Table A1. Student Characteristics under Sample Restrictions, Entering class 2008-09 Academic Year

	(1) Full Cohort mean/sd	(2) Credential Limits mean/sd	(3) Age Limits mean/sd	(4) Mode Variation Limits mean/sd
Instructional mode record				
Face-to-face classes only	0.72	0.70	0.70	0.59
	(0.45)	(0.46)	(0.46)	(0.49)
Both modes	0.24	0.26	0.26	0.37
	(0.43)	(0.44)	(0.44)	(0.48)
Distance classes only	0.04	0.04	0.03	0.04
	(0.19)	(0.18)	(0.18)	(0.19)
Student characteristics				
Ever takes basic courses	0.38	0.38	0.38	0.42
	(0.48)	(0.48)	(0.49)	(0.49)
Ever receives financial aid	0.51	0.53	0.53	0.58
	(0.50)	(0.50)	(0.50)	(0.49)
First-term GPA	2.23	2.20	2.17	2.19
	(1.35)	(1.33)	(1.33)	(1.28)
Units attempted first term	7.72	8.06	8.19	9.24
	(4.55)	(4.51)	(4.46)	(4.24)
Observed in Multiple Colleges	0.01	0.01	0.01	0.01
	(0.10)	(0.10)	(0.10)	(0.11)
Modal goal: Transfer	0.44	0.48	0.49	0.54
	(0.50)	(0.50)	(0.50)	(0.50)
Modal goal: AA no transfer	0.06	0.06	0.06	0.06
	(0.24)	(0.24)	(0.23)	(0.23)
Modal goal: Vocational	0.14	0.12	0.11	0.08
	(0.34)	(0.33)	(0.32)	(0.27)
Modal goal: Unknown	0.29	0.28	0.28	0.28
	(0.45)	(0.45)	(0.45)	(0.45)
Modal goal: Personal interest	0.05	0.05	0.05	0.04
	(0.22)	(0.21)	(0.21)	(0.20)
Modal goal: Basic skills	0.02	0.01	0.01	0.01
	(0.15)	(0.12)	(0.11)	(0.09)
Age at first CCC term	23.86	22.61	21.03	20.31
	(22.73)	(18.69)	(4.79)	(4.19)
Female	0.49	0.49	0.49	0.52
	(0.50)	(0.50)	(0.50)	(0.50)
Hispanic	0.36	0.37	0.38	0.36
	(0.48)	(0.48)	(0.48)	(0.48)
White	0.29	0.30	0.30	0.31

	(0.45)	(0.46)	(0.46)	(0.46)
Asian	0.09	0.08	0.08	0.08
	(0.29)	(0.26)	(0.27)	(0.28)
Black	0.10	0.10	0.10	0.10
	(0.30)	(0.30)	(0.30)	(0.29)
Other race	0.16	0.15	0.15	0.15
	(0.36)	(0.36)	(0.36)	(0.35)
Degree credentials at first term of entry				
No high school credential	0.07	0.00	0.00	0.00
	(0.26)	(0.00)	(0.00)	(0.00)
High school diploma	0.71	0.91	0.91	0.93
	(0.45)	(0.29)	(0.28)	(0.26)
GED	0.06	0.08	0.07	0.06
	(0.24)	(0.27)	(0.26)	(0.24)
CA HS Proficiency	0.01	0.02	0.01	0.01
	(0.11)	(0.12)	(0.11)	(0.11)
Foreign HS diploma	0.04	0.00	0.00	0.00
	(0.20)	(0.00)	(0.00)	(0.00)
Prior post-secondary degree	0.10	0.00	0.00	0.00
	(0.30)	(0.00)	(0.00)	(0.00)
	(44.80)	(39.47)	(38.75)	(33.70)
Course outcomes				
% of classes completed	80.78	80.56	80.23	80.75
	(27.90)	(27.22)	(27.30)	(24.18)
% of attempted classes student received A/B/C/P	69.92	69.35	68.51	68.83
	(35.17)	(34.54)	(34.73)	(32.36)
% of classes attempted for grades student received A/B	49.40	48.12	47.22	47.40
	(37.25)	(36.35)	(36.17)	(33.85)
Unique students	440,405	358,013	316,941	217,194

Means (SD) given. Credential Limits includes sample only with high school (but no higher) credentials. Age Limits excludes students <18 and >40 at first term

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