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The impact of online learning on students' course outcomes: Evidence from a large community and technical college system

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ABSTRACT

Using a large administrative dataset from a statewide system including 34 community and technical colleges, the authors employed an instrumental variable technique to estimate the impact of online versus face-to-face course delivery on student course performance. The travel distance between each student's home and college campus served as an instrument for the likelihood of enrolling in an online section of a given course. In addition, college-by-course fixed effects controlled for within- and between-course selection bias. Analyses yield robust negative estimates for online learning in terms of both course persistence and course grade, contradicting the notion that there is no significant difference between online and face-to-face student outcomes—at least within the community college setting. Accordingly, both two-year and four-year colleges may wish to focus on evaluating and improving the quality of online coursework before engaging in further expansions of online learning.

1. Introduction

For two decades, state financing of higher education has been on the decline (Kane, Orszag, & Gunter, 2003). Public postsecondary institutions have responded by raising tuition, increasing class sizes, cutting programs, and otherwise seeking to reduce costs and improve efficiency. At the same time, colleges have sharply increased their distance education offerings through online coursework—though often with an intent to improve access and convenience for students rather than to reduce costs. In the wake of the recent recession, policy leaders in several states, assuming that online courses must be more cost-effective than face-to-face courses, have championed further expansions in online learning (e.g., Chen, 2012; Fain & Rivard, 2013; Texas Higher Education Coordinating Board, 2011). The notion that online courses are more cost-effective than traditional, face-to-face courses is predicated on two assumptions: first, that online course sections are consistently less expensive; and second, that they yield fairly comparable student outcomes.

Although it may seem self-evident that online courses are consistently cheaper than face-to-face courses, there is surprisingly little evidence on online and face-to-face course costs. Most research on the topic is dated (e.g., Hawkes & Cambre, 2000; Jewett, 2000; Jung, 2003; Levine & Sun, 2002; Rogers, 2001; Virginia Community College System, 2001; Whalen & Wright, 1999), and the conclusions drawn from relevant studies are mixed. Rumble (2003) discussed the complexities involved in making generalizations about costs across different types of courses and institutions and concluded that there can be no clear-cut answer as to whether online courses are

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indeed cheaper. Schiffman (2005) noted that development costs for online courses varied across institutions from $10,000 to $60,000 per course. Based on interviews with presidents, provosts, and other senior academic leaders at more than 25 higher education institutions,[1] Bacow, Bowen, Guthrie, Lack, and Long (2012) reported that most institutions provided distance education to better serve student needs rather than to save on costs. In fact, many interviewees believed that online courses were at least as expensive as traditional courses, not only due to their substantial start-up costs (e.g., investments in technology, course design, and instructor training) but also due to recurring costs (e.g., those resulting from increased coordination demands and technical support). Moreover, studies of online course costs have not taken into account the quality or effectiveness of the courses examined, and it is possible that online courses with high completion rates and strong learning outcomes require substantial investments to design and teach.

The second assumption underlying the cost-effectiveness argument—that online courses produce student outcomes comparable to those produced by face-to-face courses—is also based on relatively weak evidence. Although dozens of studies have compared student performance between online and face-to-face courses, most have been descriptive studies, with no controls for student self-selection. Moreover, the majority have focused on populations (e.g., K-12 students) or contexts (e.g., hour-long educational modules) that are not relevant to the typical online college course. Only a few random-assignment or quasi-experimental studies have focused on semester-length college courses (Caldwell, 2006; Cavus & Ibrahim, 2007; Coates, Humphreys, Kane, & Vachris, 2004; Figlio, Rush, & Lin, 2010; LaRose, Gregg, & Eastin, 1998; Mentzer, Cryan, & Teclehaimanot, 2007; Odell, Abbitt, Amos, & Davis, 1999; Peterson & Bond, 2004; Schoenfeld-Tacher, McConnell, & Graham, 2001). Results of these studies are mixed, leading many college leaders to conclude that online learning at least "does no harm." However, two considerations limit the usefulness of this conclusion.

First, nearly all previous studies have focused on learning outcomes among students who completed the course, and thus have disregarded the potential impact of online delivery on course withdrawal. Ignoring course withdrawal may be reasonable within the context of selective four-year institutions, which typically have low course withdrawal rates. In the community college context, however, descriptive studies have typically reported course withdrawal rates in the 20–30% range, with higher withdrawal rates for online courses (Beatty-Guenter, 2002; Carr, 2000; Chambers, 2002; Moore, Bartkovich, Fetzner, & Ison, 2003). Course persistence and completion is a particularly important issue in community colleges, where most students are low-income, many are working or have dependents, and few can readily afford the time or money required to retake a course they did not successfully complete the first time (Adelman, 2005; Bailey & Morest, 2006; Planty et al., 2009). Thus, studies that focus solely on course completers are minimally helpful to community college administrators contemplating the potential costs and benefits of expanding online course offerings.

Second, it is unclear whether the sets of courses examined in previous research represent the larger body of online courses available in the postsecondary setting, and particularly in the community college setting. Each study in the literature tends to focus on one or two specific courses, which in some cases are selected because they are thought to represent high-quality examples of online coursework. Moreover, each course included in the rigorous research cited above was conducted within a selective college or university (Jaggars & Bailey, 2010)—institutions that are not representative of the less-selective or open-access colleges that make up the bulk of the nation's postsecondary sector. Qualitative research conducted in the community college setting has revealed that most online instructors simply convert their face-to-face instructional materials to printed handouts and text-heavy slide presentations, with few of the interactive technologies that may effectively engage students in online learning (Cox, 2006; Edgecombe, Barragan, & Rucks-Ahidiana, 2013). Although no parallel studies have been conducted in the four-year sector, these findings raise the question of how high-quality the "typical" or "average" online college course may be.

In order to understand student performance in the typical online course within a given sector, it would be most useful to compare a large and representative set of online courses against a similar set of face-to-face courses. Thus far, only one study has done so: Using a dataset including hundreds of course sections from 23 colleges in Virginia's community college system, Xu and Jaggars (2011) found that students fared significantly worse in online courses in terms of both course persistence and end-of-course grades. However, the study was limited to entry-level English and math courses in community colleges in one state, raising the question of whether the results apply to other academic subjects and other state contexts. Moreover, although Xu and Jaggars controlled for a wide array of student, course, and institutional characteristics using multilevel propensity score matching, they could not control for unobserved influences on students' course selection, such as employment status, actual working hours, educational motivation, and academic capacity. Thus, the results could have remained subject to selection bias. Indeed, using an endogenous switching model, Coates et al. (2004) found that online students tended to have "higher levels of unobservable ability that improves their performance under both types of instruction" (p. 543). Thus, failure to account for unobservables underlying student self-selection may underestimate any negative impacts of the online format on student course performance.

This paper builds on Xu and Jaggars' (2011) study of Virginia community colleges by focusing on a different region of the country and using an instrumental variable (IV) technique to control for unobserved confounding

[1] The institutions included public and private research universities, four-year colleges, and community colleges.

variables. Using a large administrative dataset from Washington State's community and technical college system, we used the distance from a student's home to college as an instrument for the likelihood of enrolling in an online rather than a face-to-face section of a given course. We augmented the IV strategy using college-by-course fixed effects, which allowed us to compare students who took the same course but were enrolled in sections with different delivery formats, potentially controlling for biases related to within- and between-course selection. To assess the effects of taking a course online rather than face-to-face, we explored two course outcomes: (1) course *persistence*, or whether a student remained in the course through the end of the semester; and (2) final course *grade* among those who persisted to the end of the course. Our analyses yielded robust estimates of negative impacts of online learning on both course persistence and course grade. Moreover, our IV estimates were consistently stronger than the corresponding OLS estimates across all model specifications, lending support to the Coates et al. (2004) argument that students tend to be positively selected into online coursework, which may bias the negative impacts of online learning toward zero when student self-selection is not well addressed.

2. Data

2.1. Data and institutional characteristics

The study used an administrative dataset of students who initially enrolled in one of Washington State's 34 two-year public community or technical colleges during the fall term of 2004. These first-time college students were tracked for approximately five years, through the summer of 2009. The dataset, provided by the Washington State Board of Community and Technical Colleges, included information on student demographics[2]; institutions attended; transcript data on courses taken and grades received; and information on each course, such as course number, course subject, and course delivery format.[3] The dataset also included information from Washington State Unemployment Insurance wage records, which allowed us to control for students' working status and working hours in each term.

The system's dataset does not include courses dropped early in the semester (prior to the course census date, or the 10th instructional day after the quarter begins). After the census date, students are not entitled to full refund if they drop the course. Those who choose to drop after that point receive a grade of "W," indicating withdrawal. Thus, in our study, "course withdrawal" denotes that a student paid tuition for a course but officially dropped prior to the term's end. "Course persistence" indicates that a student formally remained through the end of the term—although some may have informally chosen to desist work in the course and thus received a failing grade. Students who persisted in each course received a grade ranging from 0.0 to 4.0.[4]

The 34 Washington community colleges have widely varying institutional characteristics. The system comprises a mix of large and small schools, as well as institutions located in rural, suburban, and urban settings. Most colleges are comprehensive (offering both transfer-oriented and occupationally oriented degrees), but five are technical colleges that primarily offer occupational degrees. Table 1 describes the 34 colleges' institutional characteristics in fall 2004, based on statistics reported to the Integrated Postsecondary Education Data System (IPEDS) database. Compared to the national sample,

Table 1
Characteristics of Washington State Community and technical colleges vs. All U.S. public two-year colleges.

Variables	All U.S. public two-year colleges	Washington state two-year colleges
Student demographics		
% White	65.89	67.06
	(23.69)	(12.96)
% Black	14.22	3.82
	(17.02)	(3.11)
% Hispanic	8.54	5.68
	(13.67)	(5.67)
% Receive federal financial aid	43.94	27.94
	(18.71)	(10.63)
% Enrolled full-time	64.53	64.93
	(11.87)	(6.71)
Academics		
Graduation rates	29.03	32.79
	(19.42)	(10.95)
First-year retention rates	57.73	57.85
	(13.85)	(9.76)
Expenditures (dollars per FTE)		
Instructional	5261.52	4848.71
	(20,987.74)	(2133.11)
Academic	1003.05	578.26
	(4365.67)	(229.78)
Institutional	1684.28	1302.03
	(4236.92)	(1391.40)
Student	1037.52	1237.12
	(1378.74)	(1544.99)
Location		
Urban	39.40%	59.38%
Suburban	23.72%	21.88%
Rural	36.81%	18.75%
Observations (*N*)	1165	34

Source: Statistics reported to the 2004 Integrated Postsecondary Education Data System (IPEDS) database.
Note: Standard deviations for continuous variables are in parentheses.

[2] In addition to information on the set of demographic characteristics available in most administrative datasets (e.g., gender, race, age, and financial aid receipt), the dataset included information on socioeconomic status (SES). Students were divided into five quintiles of SES based on census data on the average income in the census block in which the student lived.

[3] The system divides course sections into three categories: face-to-face, online, and hybrid. Given that less than 2% of courses were offered in a hybrid format, and that these courses included a substantial on-campus component (i.e., online technology displaced at most 50% of the course delivery), we combined the hybrid and face-to-face formats in this analysis. In a robustness check, we excluded all hybrid courses from the analysis; the results are nearly identical to those presented in Tables 1–4.

[4] Each student's grade is recorded to one decimal place.

Washington's community and technical colleges are more likely to be located in urban areas and serve lower proportions of African American and Hispanic students, as well as lower proportions of students who receive federal financial aid.

2.2. Sample description

A major assumption underlying the use of distance as an instrument (discussed further in Section 3) is that students do not choose where to live based on unobserved confounding variables that influence both online enrollment and course outcomes. One such potential confounding variable is educational motivation, which may be particularly relevant in the context of community colleges, given the wide variation in their students' educational intent (Alfonso, 2006; Alfonso, Bailey, & Scott, 2005). To address this concern, we focused on in-state students enrolled in an academic transfer-oriented track (N = 22,624), who intended to eventually transfer to a four-year school and earn a bachelor's degree. Among these students, 95% lived within 65 miles of their college, with an average distance of 17 miles.[5]

Because our goal was to understand the impact of online versus face-to-face delivery *within* specific courses, we excluded courses where all sections were offered through the same delivery format. That is, all courses in our analysis were offered through both online and face-to-face sections. In addition, we excluded developmental education (or "remedial") courses, given that very few of them were offered online. Finally, a handful of courses (<0.003%) were taken at a school that was not the student's primary college, raising the concern that distance could be endogenous in these cases. To be conservative, we dropped those courses from analysis.[6]

The final analysis sample included 125,218 course enrollments among 18,567 students; approximately 22% of enrollments were in online sections. Student summary statistics are displayed in Table 2. In addition to the statistics for the full student sample (column 1), the table presents the characteristics of students who ever attempted an online course across the five-year period of study ("ever-online" students, column 2) and the characteristics of students who never took an online course during that period (column 3). On a descriptive basis, it appears that the ever-online student population was comprised larger proportions of females, White students, students of higher socioeconomic status (SES), students who applied and were eligible for need-based aid, students who lived slightly farther away from their college of attendance, and students who worked more hours in a term. The ever-online student sample also seems to have had a higher level of academic preparedness; larger proportions of ever-online students were dual enrolled prior to college, and ever-online students had higher grade point averages (GPA) and had earned more credits by the end of their first term.[7] These statistics imply that students with stronger academic preparation were more likely to attempt an online section of a given course. However, it is also possible that more prepared students tended to take courses in certain subjects that also happened to have more online sections. To account for this possibility, we used academic subject fixed effects to control for student self-selection into different subject areas (see Section 3.1 for details).

2.3. Online courses in Washington community and technical colleges

Washington's community and technical college system provides a number of supports intended to create an environment conducive to high-quality online learning. In 1998, the system implemented several supports for students in online courses (including an online readiness assessment, a course management system tutorial, and online technical support services) as well as supports for instructors (including required training on the online course management system and voluntary training on effective online pedagogies, advanced technological tools, and other topics).

As in most community college systems (see Cox, 2006), however, each Washington institution developed its online program locally, according to the college's own priorities and resources and the perceived needs of its particular student population. Accordingly, colleges varied considerably in the proportion of online course enrollments (ranging from 10% to 37%). Colleges also exerted local control over course quality standards, instructor evaluations, and campus-level supports for online students and faculty. These varying practices, together with varying student characteristics and programs across colleges, likely contribute to variation in online course outcomes. For example, average online course persistence rates ranged from 84% to 96% across colleges, and online course grades ranged from 1.54 to 2.97. This school-level variation highlights the importance of controlling for school-level effects in our analysis.

Across the five-year period of the study, online course-taking increased substantially. In the fall of 2004, entering students attempted an average of 1.03 credits online (12% of their term credits); by the spring of 2009, still-enrolled students in the 2004 cohort had more than doubled their rate of online credit attempts to an average of 2.56 credits (39% of their term credits). This growth was due to two separate trends. First, students in the 2004 cohort were increasingly likely to try at least one online course over

[5] About 1% lived a considerable distance from their college (≥182 miles). Given that some of these students also took face-to-face courses at the college, some may have provided their parents' home address rather than their own address. We excluded these students in a robustness check and the results remained consistent.

[6] In a separate robustness check, we included those courses in the analysis, and the results were almost identical to those presented in Tables 1–4.

[7] Although first-term GPA provides a useful sense of students' initial academic performance, it could be affected by students' choices of online versus face-to-face formats during their first term. However, less than 13 percent (N = 2376) of our sample took an online course in their first term, and when we excluded these students from our analysis, the academic advantage in first-term GPA persisted for ever-online students.

Table 2
Summary statistics.

(I) Student-level characteristics				
	Full student sample	Ever online student sample	Never online student sample	Diff (ever–never)
Demographic characteristics				
Female	0.525	0.571	0.475	0.096***
	(0.499)†	(0.495)	(0.499)	
White	0.697	0.710	0.682	0.028***
	(0.460)	(0.454)	(0.466)	
African American	0.044	0.037	0.052	−0.015***
	(0.205)	(0.188)	(0.222)	
Hispanic	0.022	0.021	0.024	−0.003
	(0.148)	(0.143)	(0.154)	
American Indian	0.014	0.012	0.017	−0.005***
	(0.118)	(0.108)	(0.129)	
Asian	0.075	0.077	0.074	0.003
	(0.264)	(0.266)	(0.262)	
Alaska Native	0.001	0.001	0.001	0.000
	(0.034)	(0.029)	(0.038)	
Native Hawaiian	0.004	0.004	0.004	0.000
	(0.060)	(0.059)	(0.062)	
Pacific Islander	0.002	0.001	0.004	−0.003***
	(0.050)	(0.035)	(0.062)	
Multiracial	0.041	0.042	0.041	0.001
	(0.199)	(0.200)	(0.198)	
Unknown race	0.062	0.061	0.064	−0.003
	(0.242)	(0.239)	(0.245)	
Age	21.304	21.444	21.151	0.293***
	(6.585)	(6.641)	(6.521)	
Eligible for need-based aid	0.421	0.444	0.397	0.047***
	(0.494)	(0.497)	(0.489)	
Highest SES	0.177	0.188	0.165	0.023***
	(0.382)	(0.391)	(0.371)	
Higher SES	0.223	0.229	0.218	0.011*
	(0.417)	(0.420)	(0.413)	
Middle SES	0.206	0.202	0.211	−0.009
	(0.405)	(0.402)	(0.408)	
Lower SES	0.180	0.176	0.185	−0.009
	(0.385)	(0.381)	(0.388)	
Lowest SES	0.137	0.131	0.145	−0.014***
	(0.344)	(0.337)	(0.351)	
Unknown SES	0.076	0.074	0.078	−0.004
	(0.265)	(0.263)	(0.267)	
Hours worked per week	14.889	15.536	14.187	1.349***
	(13.380)	(13.201)	(13.357)	
Distance to college (miles)	17.248	17.537	16.935	0.602***
	(13.895)	(14.228)	(13.519)	
Academic characteristics				
Took developmental ed.	0.601	0.594	0.607	−0.013*
	(0.490)	(0.491)	(0.489)	
Limited English proficiency	0.002	0.002	0.002	0.000
	(0.040)	(0.041)	(0.040)	
Dual enrolled prior to entry	0.087	0.094	0.080	0.014***
	(0.282)	(0.292)	(0.272)	
GPA in first term††	2.888	2.981	2.784	0.197***
	(0.947)	(0.872)	(1.014)	
Credits accrued first term	11.200	11.633	10.731(4.963)	0.902***
	(4.857)	(4.717)		
Credits taken per term	12.847	13.033	12.650	0.383***
	(3.302)	(3.109)	(3.484)	
Observations	18,567	9655	8912	

(II) Course-level characteristics and outcomes				
	Full course sample	Online course sample	Face-to-face course sample	Diff (ever–never)
Online delivery format	0.218	1.000	0.000	–
	(0.413)	(0.000)	(0.000)	
Course persistence	0.933	0.907	0.941	−0.034***
	(0.249)	(0.293)	(0.235)	
Course grade†††	2.652	2.539	2.682	−0.143***
	(1.281)	(1.416)	(1.240)	
Observations	125,218	27,331	97,887	

* Significant at the 10% level.
*** Significant at the 1% level.
† Standard deviations are in parentheses.
†† For "GPA at the end of first term" $N = 17,355$ for the full course sample, $N = 9170$ for the ever online student sample, and $N = 8185$ for the never online student sample.
††† For "course grade" $N = 116,830$ for the full course sample.

time. Second, among only students who were actively online in a given term, the percentage of credits taken online also increased across terms. To account for growth over time, we include controls for term-level variation in our analysis.

3. Methods

3.1. Basic empirical model

To assess the effects of online course delivery, we used regression techniques, beginning with a probit model for course persistence and an OLS model for course grade. Our basic strategy related student *i*'s course outcomes in subject *k* at campus *j* in term *t* to the course format in the following equation (using course grade as an example):

$$Y_{itkj} = \alpha + \beta\, online_{itkj} + \gamma X_i + \pi_t + \rho_k + \sigma_j + \mu_{itkj} \quad (1)$$

In this equation, *online* is the key explanatory variable and is equal to 1 if the course is taken online. We incorporated a rich set of controls into our model, where X_i includes demographic attributes (e.g., age, gender, race, and SES), academic preparedness (e.g., remedial status, and previous dual enrollment), and semester-level information (e.g., working hours in current term, total credits taken in current term).[8] In addition, we included fixed effects for the term of enrollment in the course (π_t), the subject of the course (ρ_k), and the campus of attendance (σ_j).

3.2. Addressing between-course selection using a college-by-course fixed effects approach

By including college, term, and course subject fixed effects, Eq. (1) addresses two potential problems related to student selection of online courses. First, students may choose course subjects based on their preference for online or face-to-face course formats. For example, if a campus offers sociology but not psychology online, then a student who prefers to take online courses may choose to fulfill his or her social science requirement with the online sociology course rather than the face-to-face psychology course. Second, online courses may be more prevalent within particular colleges, terms, departments, or course subjects. Thus, for example, students enrolled in an English program may be more likely to enroll in online courses than those in an engineering program.

Although Eq. (1) addresses these issues, it cannot account for a potential third problem: Certain courses (even within a particular college, term, and subject) may be more likely to be offered online. For example, suppose that within a given department, advanced courses were more likely to be offered online than entry-level courses. A direct comparison of online and face-to-face sections across these courses would then result in biased estimates. To address this problem, we used an additional model that used college-by-course fixed effects with term fixed effects, thus effectively comparing online and face-to-face sections of the same course.[9]

3.3. Addressing within-course selection using an instrumental variable approach

Although college-by-course fixed effects are an effective means of controlling for student self-selection into different courses, there may be some remaining selection issues if students systematically sort between online and face-to-face sections of a single course. To deal with this concern, we employed an IV approach, using a variable related to the treatment but theoretically unrelated to the outcome to identify the treatment effect. In this analysis, we used the distance from each student's home to their college campus as an instrument for the student's likelihood of enrolling in an online rather than face-to-face section. Specifically, we first identified the associated geocode for each address in the dataset, including both student home address and college address; we then used Google Maps to calculate the "travel distance" between each student's home and their college of attendance. Given that online courses offer the flexibility of off-site education, students who live farther from their own college campus might be more likely to take advantage of online courses, compared with students who live closer to their college. Using distance as an instrumental variable, we modified Eq. (1) to use an IV approach. Specifically, we first predicted the probability that an individual *i* took a particular course *c* online using a probit model:

$$\begin{aligned} \text{Prob}\,(online_{ict}) = \Phi(&\alpha + \delta_1 distance_i + \delta_2 distance_i^2 \\ &+ \gamma X_i + +\pi_t + Z_c + \mu_{ict}) \end{aligned} \quad (2)$$

where Φ represents the cumulative density function for the standard normal distribution and Z_c represents college-by-course fixed effects. Consistent estimates of the relative impact of online course delivery can be then derived by using the estimated probabilities from Eq. (2) as instruments for the endogenous dummy variable $online_{ict}$ in a 2SLS estimation process.[10]

There are four potential concerns with using distance as an instrument. First, researchers (e.g., Long & Kurlaender, 2009) have argued that distance may be a problematic instrument when using national datasets because of differences in the way distance is perceived across the country. This concern is limited in the current context, given that we focused on one state; in our sample, the average distance from a student's home to the college of attendance was 17 miles, with nearly 90% of students

[8] The full list of covariates includes dummy variables for gender, race, socioeconomic status, receipt of federal financial aid, limited English proficiency, dual enrollment prior to college, whether the student enrolled in a remedial course, and whether the student was enrolled full-time in the given term. Continuous variables include the total number of credits enrolled in that term and total working hours in that term.

[9] Each college-by-course fixed effect includes the subject area and college of attendance (for example, "coll101math111"). Thus academic subject and college fixed effects become redundant and are automatically dropped when college-by-course fixed effects are added to the model.

[10] See Wooldridge (2002) for a detailed discussion about using nonlinear models in the first stage instrumental variable analysis. Similar procedures are also illustrated in Coates et al. (2004).

living within 25 miles. It is unlikely that perceptions of distance would be fundamentally different within such a small range. In addition, given the mountainous terrain in Washington State, where short distances may translate into long commutes, we used travel distance rather than direct-line distance. Moreover, we also used a nonlinear probit model and added a quadratic term (δ_2) into the first-stage IV equation to take into account the possibility that the relationship between travel distance and the probability of online enrollment may not be linear.

Second, one might be concerned about potential endogeneity issues in terms of travel distance. Some researchers have suggested that individuals or families who value education might choose to live near a college campus (e.g., Card, 1995; Long & Kurlaender, 2009; Rouse, 1995); similarly, the quality of a student's previous high school instruction might vary systematically with the high school's distance from the nearest college. Moreover, students who live close to college campus may be able to access support services more readily, which could heighten their academic success. Our sample limitation (including only students who were homogeneous in their intent to earn a four-year degree) may limit the impacts of such factors; however, to more rigorously assess their potential impacts, we also conducted a validity check by assessing the relationships between course outcomes and distance for a sample of face-to-face courses (see Section 4.3).

Third, using an instrumental variable strategy may be more appropriate for examining course completion among all students who enrolled in a course than for examining course grades among those who persisted in the course. Examining the outcome of course grades only among persisters may introduce additional self-selection bias, if persistence rates differ by course delivery format. However, as discussed in Section 4, online courses have higher attrition rates, which may leave online courses with relatively better-prepared students by the end of the course. Thus, using grades conditional on persistence as the outcome is likely to underestimate rather than overestimate the negative effect of online delivery on students' grades.

Finally, distance will be effective as an instrumental variable only if it has a relationship to online course enrollment. We explore this issue in Section 4.2.

4. Results

4.1. Ordinary least squares estimates

In descriptive terms, across the total sample of 125,218 course enrollments the overall course persistence rate was 93%, with a gap between online courses (91%) and face-to-face courses (94%). For enrollments that persisted until the end of the semester ($N = 116{,}830$), the average grade was 2.65 (on a 4-point scale), also with a gap between online courses (2.54) and face-to-face courses (2.68).[11]

[11] Please see the bottom panel in Table 2 for the standard deviation of each outcome variable by course delivery format.

Table 3
OLS/probit estimates of the impact of the online format (and each covariate) on course persistence and course grade.

	Course persistence	Course grade
	Coefficient (SE)	Coefficient (SE)
Online delivery format	−0.257***	−0.197***
	(0.018)	(0.018)
(Marginal effect)	−0.036***	–
	(0.003)	
Covariates: demographic characteristics		
Female	0.007***	0.198***
	(0.002)	(0.009)
African American	−0.014***	−0.464***
(base group: White)	(0.005)	(0.024)
Hispanic	−0.017***	−0.169***
	(0.007)	(0.038)
American Indian	−0.020***	−0.257***
	(0.008)	(0.040)
Asian	−0.006**	−0.021
	(0.003)	(0.018)
Alaska Native	−0.097***	−0.627***
	(0.039)	(0.141)
Native Hawaiian	−0.032**	−0.168***
	(0.016)	(0.063)
Pacific Islander	−0.036**	−0.544***
	(0.021)	(0.097)
Multi-racial	−0.014***	−0.225***
	(0.004)	(0.023)
Unknown race	0.002	0.041**
	(0.003)	(0.019)
Age	0.000	0.024***
	(0.000)	(0.001)
Eligible for need-based aid	0.017***	0.081***
	(0.002)	(0.010)
Higher SES (base group:	−0.003	−0.041***
highest SES)	(0.002)	(0.014)
Middle SES	−0.010***	0.002
	(0.003)	(0.016)
Lower SES	−0.001	−0.013
	(0.003)	(0.017)
Lowest SES	−0.014***	−0.121***
	(0.003)	(0.019)
Unknown SES	0.005	0.045**
	(0.004)	(0.021)
Hours worked per week	−0.000***	−0.002***
	(0.000)	(0.000)
Covariates: academic characteristics		
Took developmental education	−0.003	−0.141***
	(0.002)	(0.011)
Limited English proficiency	0.026	0.198**
	(0.013)	(0.083)
Dual enrolled prior to entry	−0.002	0.127***
	(0.003)	(0.016)
Credits taken this term	−0.001***	0.019***
	(0.000)	(0.003)
Enrolled full time this term	0.012***	−0.048**
	(0.003)	(0.019)
Observations	125,218	116,830

Notes: Because the data include multiple observations within each course, standard errors for all models are adjusted for clustering at the course level.
See Wooldridge (2003) for a detailed discussion of the necessity and methods of adjusting standard errors when individual observations are clustered.
We used the student-level variable "average credits taken per term" in Table 1 to describe student sample characteristics; in the regression analysis on the course-level sample, we used the course-level variable of the actual number of credits enrolled in the given term as the covariate.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4
Estimates of the effect of taking a course online, based on different model specifications.

	OLS/probit estimates			IV estimates		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: course persistence						
Online format (SE)	−0.257***	−0.298***	−0.311***	−0.420***	−0.457***	−0.509***
	(0.018)	(0.017)	(0.017)	(0.118)	(0.126)	(0.132)
Marginal effect (SE)	−0.036***	−0.041)***	−0.044***	−0.054***	−0.058***	−0.065***
	(0.003)	(0.003)	(0.003)	(0.016)	(0.017)	(0.018)
Dependent variable: course grade						
Online format (SE)	−0.196***	−0.233***	−0.266***	−0.228***	−0.270***	−0.324***
	(0.018)	(0.017)	(0.016)	(0.089)	(0.098)	(0.110)
College and subject FE	No	Yes	Yes	No	Yes	Yes
Year-term FE	No	Yes	Yes	No	Yes	Yes
College-by-course FE	No	No	Yes	No	No	Yes

Notes: $N = 125, 218$ for the analysis on course persistence; $N = 116, 830$ for the analysis on course grade. Standard errors for all models are adjusted for clustering at the course level. Each cell represents a different regression specification. All models also include the following covariates: gender, ethnicity dummy variables, socioeconomic status dummy variables, receipt of federal financial aid, limited English proficiency, dual enrolled prior to college, ever enrolled in remedial courses, total credits taken in that term, total working hours in that term, and full-time (vs. part-time) college enrollment in that term.
*** Significant at the 1% level.

Table 3 presents baseline probit and OLS estimates of the relationship between online course format and the outcomes of course persistence and course grade. The regression includes the vector of student characteristics X_i but does not include any fixed effects. The results suggest that the online course format had a significant negative relationship with both course persistence and course grade. Converting the probit coefficient ($\beta = -0.257$) for course persistence to a marginal effect[12] indicates that online course persistence rates were 3.6 percentage points lower than face-to-face persistence rates. Among students who persisted through the course, the average grade in online courses was approximately 0.19 points lower than in face-to-face courses.

Table 3 also shows the estimated coefficients for the controls in the model. Overall, women, full-time students, older students, and those eligible for financial aid tended to perform better academically, while ethnic minority and low-income students and those working more hours per week tended to perform worse.

The left panel of Table 4 contrasts the baseline estimates for online learning with the estimates from the fixed-effects models. When fixed effects for college, course subject, and term were included (column 2), the estimated negative relationship became larger for both outcome measures; when college-by-course fixed effects were included (column 3), the gaps between online and face-to-face outcomes were further magnified to −4.4 percentage points for course persistence and −0.26 grade points for course grade.

4.2. Instrumental variable estimates

To control for selection into online coursework based on unobservable student characteristics, our IV strategy used the distance between a student's home and college of

Table 5
Results of probit model for first-stage IV (probability of taking a course online).

	(1)	(2)	(3)
Distance to college (SE)	0.025***	0.025***	0.022***
	(0.001)	(0.001)	(0.001)
Marginal effect (SE)	0.007***	0.007***	0.006***
	(4.28e−04)	(3.86e−04)	(2.74e−04)
Distance squared (SE)	−1.01e−04***	−9.82e−05***	−7.76e−05***
	(1.01e−05)	(9.76e−06)	(7.52e−06)
Marginal effect (SE)	−2.90e−05***	−2.71e−05***	−2.34e−05***
	(2.89e−06)	(2.65e−06)	(1.88e−06)
College and subject FE	No	Yes	Yes
Year-term FE	No	Yes	Yes
College-by-course FE	No	No	Yes
F-Test on excluded	497.32	557.87	471.50
Instruments (Prob > *F*)	<0.001	<0.001	<0.001

Notes: $N = 125, 218$. Standard errors for all models are adjusted for clustering at the course level. Each cell represents a different regression specification. All models also include the following covariates: gender, ethnicity dummy variables, socioeconomic status dummy variables, receipt of federal financial aid, limited English proficiency, dual enrolled prior to college, ever enrolled in remedial courses, total credits taken in that term, total working hours in that term, and full-time (vs. part-time) college enrollment in that term.
*** Significant at the 1% level.

attendance as an instrument for the likelihood of enrolling in an online rather than face-to-face section of a particular course controlling for all other available covariates. Table 5 shows the first-stage results using Eq. (2) and indicates that the travel distance between a student's home and college is a significant and positive predictor of online enrollment across all models. The quadratic term is significantly negative though small in magnitude, indicating that while students who live farther from their own

[12] Calculated by averaging the derivative at each observation.

college campus are more likely to take advantage of online courses compared with students who live closer to their college, this positive relationship between distance and online enrollment becomes less strong as distance increases.[13] We conducted *F*-tests on the excluded instrument to test its strength,[14] and our results indicated that travel distance does indeed help explain which students choose online course sections after controlling for all other covariates, no matter which model specification is employed.

However, for the IV estimates to be consistent, it must also be the case that travel distance is uncorrelated with the error term. As a validity check, we excluded all online courses from the sample and examined the relationship between course outcomes and distance for the subsample of face-to-face courses.[15] If students living closer to campus were systematically more motivated, received better instruction in high school, or had better access to school resources, then distance would be directly related to course outcomes for this subsample. The results of this exploration, which are robust to all model specifications, suggest no relationship between course outcomes and distance for face-to-face courses. This evidence of independence strengthens our interpretation that the IV estimates reflect the impact of course delivery format on course outcomes.

The right panel in Table 4 shows the IV estimates for online learning in terms of each course outcome measure. The results echo the OLS estimates: The online course format had a negative estimate for both course persistence and course grade, and the impacts became stronger when we added fixed effects. In addition, the IV estimates are noticeably and consistently stronger than the corresponding OLS estimates using each model specification. For course persistence, the marginal effect derived from the IV estimate controlling for all fixed effects (column 6) is −0.07, compared with −0.04 based on the OLS model. For course grade, the column 6 estimate is −0.32, compared with −0.27 based on the OLS model. The magnification of the estimates after controlling for both observed and unobserved characteristics supports the notion that online courses are more popular among more motivated and academically better prepared students. As a result, straightforward OLS estimates may be subject to a downward bias when precise measures of academic ability and motivation are unavailable.

4.3. Robustness checks

Given that the colleges in our sample varied widely in terms of their enrollment sizes and in the proportion of course enrollments that were online, we conducted two robustness checks to ensure that our results did not reflect the effectiveness of online courses in particular schools. We reran analyses based on a sample excluding the three colleges with the largest student enrollments, as well as on a sample excluding the three colleges with the largest online enrollments. Despite small variations, the results were similar to those presented in Table 4.

Another potential concern is that our results may be driven by a small set of individuals who took an entirely online curriculum or a high proportion of courses online. Yet among the 18,567 students in the sample, only 3% ($N = 574$) took all of their courses online; most students who attempted online courses enrolled in them intermittently, or as one course among several face-to-face courses. In addition, the majority of "fully online" students took no more than three online courses before they dropped out from the college. The courses taken by these students ($N = 1778$) make up only 1% of the full course sample, and thus should not exert a large impact on the estimates. As a robustness check, however, we excluded all fully online students from the sample, and the results were nearly the same as those presented in Table 4.

In a similar vein, we considered the possibility that our results were driven by a few large courses that offered a high number of online sections. To address this concern, we restricted the data to courses in which at least 30% of enrollments were in face-to-face sections ($N = 120{,}066$) and reran the analysis on this subsample. Despite minor variations in the coefficients, the results were qualitatively similar to those presented in Table 4.

A final concern with our analysis is that we relied primarily on a cohort that entered college nearly a decade ago, in 2004. The advantage of examining this cohort is that it supplies several years of data for each student, making the college-by-course fixed effects strategy more plausible. The disadvantage is that online course technologies may have evolved since these students entered college, resulting in improved outcomes vis-à-vis face-to-face courses. To investigate this possibility, we examined changes over time in course outcomes. Descriptive data shown in Fig. 1 suggest that although course outcomes varied over time, the gap in performance between online and face-to-face outcomes remained fairly consistent. To conduct a more explicit test of whether the gap remained consistent, we added interaction terms between year dummies and online format into the model shown in column 6 of Table 4. We used an *F*-test to examine the joint statistical significance of these interaction terms; the null hypothesis—that they were jointly insignificant—failed to be rejected for either course persistence ($F = 1.20$, $p = 0.28$) or course grade ($F = 0.21$, $p = 0.93$). That is, the adjusted association between course format and student performance did not change significantly over the four-year span

[13] For example, the probability of taking a particular course online increased 0.6 percentage points when travel distance increased from 0 to 1 mile, but increased by a slightly smaller 0.5 percentage points when travel distance increased from 20 to 21 miles (based on the marginal effect from the college-by-course fixed effects model, column 3).

[14] Stock, Wright, and Yogo (2002) described a rule of thumb for estimating the strength of the instrument in models using one instrumental variable for one endogenous covariate, as in the current case: the instrumental variable is regarded as a weak predictor of the endogenous covariate if the *F*-statistic against the null hypothesis—that the excluded instrument is not a significant predictor in the first-stage equation—is less than 10.

[15] Removing online courses from the sample did not substantially curtail our student sample size or variability among the student sample in terms of distance from campus; more than 97% of students took at least one face-to-face course during their time at college.

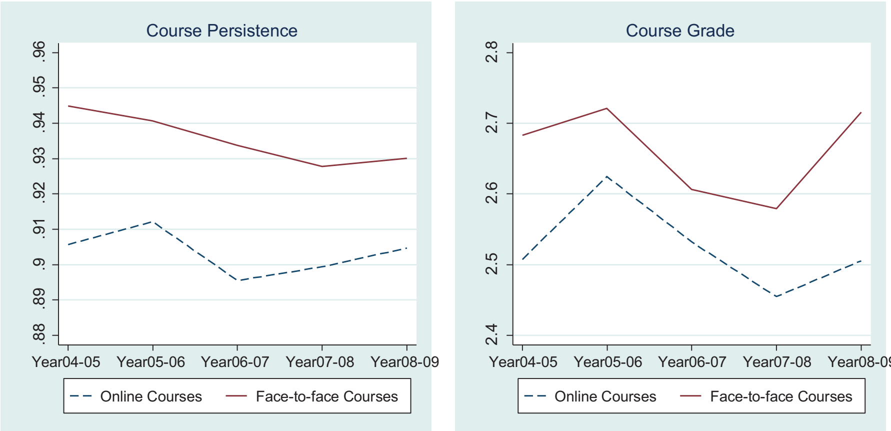

Fig. 1. Online and face-to-face course outcomes, 2004–2005 to 2008–2009.

of the study, suggesting that evolving technologies either were not adopted or did not have a strong impact on online success.

5. Discussion and conclusion

Using a unique dataset with information on a large and representative set of online courses and similar face-to-face courses, we explored the impact of online delivery on student course performance in the community college setting. Estimates across all model specifications suggest that the online format had a significant negative impact on both course persistence and course grade. This relationship remained significant even when we used an IV approach and college-by-course fixed effects to address within- and between-course selection. In practical terms, these results indicate that for the typical student, taking a particular course in an online rather than face-to-face format would decrease his or her likelihood of course persistence by 7 percentage points (e.g., from 95% to 88%), and if the student persisted to the end of the course, would lower his or her final grade by more than 0.3 points (e.g., from 2.85 to 2.52).

Some proponents of online learning argue that high withdrawal rates in online courses are due to self-selection bias (Howell, Laws, & Lindsay, 2004; Hyllegard, Heping, & Hunter, 2008). In our study, we explored the direction of the purported selection bias by comparing IV estimates with the straightforward OLS estimates; the fact that the IV estimates were consistently stronger than the corresponding OLS estimates across all model specifications suggests that students who take online courses in community colleges tend to be better prepared and more motivated. As a result, descriptive comparisons are likely to *underestimate* rather than overestimate the gap between online and face-to-face performance outcomes.

Two factors may influence the generalizability of these results to other postsecondary settings: the population of students served, and colleges' philosophies of course design and support. First, recent research (Figlio, Rush, & Yin, 2010; Kaupp, 2012; Xu & Jaggars, 2013) suggests that gaps between online and face-to-face outcomes may be stronger among less-advantaged populations—particularly among ethnic minorities and students with below-average prior GPAs. If so, then the gaps we observed in Washington State community colleges may be even wider in colleges that serve high proportions of disadvantaged students, but diminished in colleges that serve more academically prepared and socially advantaged students.

Second, some colleges may be more thoughtful than others in terms of how they design and support online courses. Well-regarded online courses are often designed through a team-based approach, with faculty collaborating with an instructional designer and often with additional support staff (Alvarez, Blair, Monske, & Wolf, 2005; Hawkes & Coldeway, 2002; Hixon, 2008; Knowles & Kalata, 2007; Puzziferro & Shelton, 2008; Thille, 2008; Xu & Morris, 2007). High-quality online courses may need to be designed to promote strong interpersonal connections, which a large body of empirical research suggests is important to students' motivation, engagement, and academic performance in the course (Bernard et al., 2009). Effective online teaching may also require explicitly developing students' time management and independent learning skills, which are thought to be critical to success in distance and online education (e.g., Bambara, Harbour, Davies, & Athey, 2009; Bork & Rucks-Ahidiana, in press; Ehrman, 1990; Eisenberg & Dowsett, 1990).

The extent to which the typical college supports its faculty in designing and teaching high-quality courses is unknown. Most community college systems, such as that in Washington State, have already expended substantial resources to support online learning. However, most of these supports are provided on a passive basis rather than proactively integrated into the everyday activities of students and faculty,[16] as recent research suggests is

[16] For example, during the timeframe under study, the Washington State system's online readiness assessment provided students with feedback as to whether an online course would be a good option for them; however, the assessment was voluntary, and many students did not take advantage of it.

necessary in order for such supports to have sustained effectiveness (Karp, 2011). In particular, studies in the community college setting suggest that most faculty are left to design online courses on their own and keenly feel a lack of training and ongoing support (Cox, 2006; Millward, 2008; Pagliari, Batts, & McFadden, 2009).

Overall, it seems likely that the applicability of our results for a given college will vary depending on the college's student population and its philosophies of course design and support. Accordingly, both two-year and four-year colleges may wish to examine the success of their own students in online and face-to-face courses, in order to identify potential gaps in performance and discuss strategies to help eliminate any such gaps.

Despite the negative results of our study, we acknowledge that online learning is an important strategy to improve course access and flexibility in higher education, with benefits from both the student perspective and the institutional perspective. From the student perspective, the convenience of online learning is particularly valuable to adults with multiple responsibilities and highly scheduled lives; thus, online learning can be a boon to workforce development, helping adults to return to school and complete additional education that otherwise could not fit into their daily routines. From an institutional perspective, online modalities allow colleges to offer additional courses or course sections to their students, increasing student access to (and presumably progression through) required courses. Given the value of these benefits, online courses are likely to become an increasingly important feature of postsecondary education. The results of this study, however, suggest that colleges need to take steps to ensure that students perform as well in online courses as they do in face-to-face courses, before continuing to expand their online course offerings.

Creating more in-depth, systematic, and proactive supports for online faculty and students may not be an inexpensive endeavor. To help clarify the costs associated with such supports, researchers should work to identify high-quality online courses and programs—those that yield strong student outcomes, particularly among disadvantaged populations—and quantify the costs associated with them. Until such research is conducted, it will remain unclear whether online courses currently do, or eventually will, represent a cost-effective alternative to face-to-face courses.

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