

**Examining the Effectiveness of Online Learning
Within a Community College System: An Instrumental Variable Approach**

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Abstract

Using a large administrative dataset from a statewide community college system, the authors employed an instrumental variable technique to estimate the impact of online versus face-to-face course delivery on student course performance, as indicated by course persistence and final course grade. To control for self-selection bias, distance from each student's home to the student's college campus was used as an instrument for the likelihood of enrolling in an online section of a given course. Course fixed effects were added to the instrumental variable model to compare students who took different sections of the same course with different delivery formats, potentially controlling for within- and between-course selection bias. Analyses yield robust negative estimates for online learning in terms of both course persistence and course grade. These results suggest that policymakers and college administrators may need to improve the quality of online learning before enacting policies that would incentivize an accelerated expansion of online enrollments.

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1. Introduction

For two decades, state financing of higher education has been on the decline (Kane & Orszag, 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 potentially 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; 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 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 whom they interviewed 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

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

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; 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 eight 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 of the eight studies focused on learning outcomes among students who completed the course, omitting the impact of course delivery format on course attrition.² This omission is striking, given that many college students do not complete their online courses. Studies of community colleges have typically reported course withdrawal rates in the 20 to 30 percent 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 focusing on course completers are

² None of these studies explored attrition as an outcome, with the exception of Caldwell (2006), who noted that no students withdrew from any of the three studied courses.

minimally helpful to community college administrators contemplating the potential costs and benefits of expanding online course offerings.

Second, it is unclear whether the small set of courses examined in the eight studies represents the larger body of online courses available in the college setting. Each study focused on a very small number of students, who were often enrolled in a course taught by the study's author. Moreover, each course was conducted within the setting of a selective college or university (Jaggars & Bailey, 2010)—institutions that are not representative of the less selective and open-access colleges that make up the bulk of the nation's postsecondary sector. Indeed, open-access two-year colleges have been particularly enthusiastic about expanding their online course offerings, primarily in order to improve the flexibility and convenience of course-taking for their large populations of nontraditional students (Parsad & Lewis, 2008).

In order to understand student performance in the typical online course, 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 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 of this study may still be subject to selection bias.

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 variables. Using a large administrative dataset from Washington State's community 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 face-to-face section of a given course. We augmented the IV

strategy using 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) whether a student remained in the course through the end of the semester, and (2) final course grade among those who persisted through the end of the course.

Our analyses yielded robust estimates of negative impacts of online learning on both course persistence and course grade. Descriptive comparisons between students who ever attempted online courses and students who took only traditional classroom courses indicated that online course takers tended to have stronger academic preparation. Thus, straightforward ordinary least squares (OLS) estimates may underestimate the negative impacts of the online format on course outcomes when accurate measures of academic ability and motivation are unavailable. Indeed, in this study, the IV estimates, which address unmeasured factors that may influence both course enrollment and outcomes, are consistently stronger than the corresponding OLS estimates across all model specifications.

The results of the current study, therefore, make several important contributions to the existing literature on distance learning in higher education. First, using an IV strategy combined with course fixed effects, this study provides the first quasi-experimental estimate of the impact of online courses in open-access colleges, based on a large, representative set of courses across multiple institutions. Second, our paper compares the IV estimates to the benchmark OLS estimates; differences in these estimates shed light on the presence, the direction, and the potential source of selection bias present in less well-controlled studies comparing online and face-to-face course formats. Finally, we explicitly examined course persistence as a distinct student outcome in addition to the more typically measured outcome of course performance among completers, thus providing additional information to college administrators who are contemplating the potential costs and benefits of expanding semester-length online course offerings.

The remainder of this paper is organized as follows: Section 2 describes the sample; section 3 introduces our empirical strategies; section 4 presents the results based on both OLS and IV models; and section 5 discusses the implications of the findings and presents policy recommendations.

2. Data

2.1 Data and Institutional Characteristics

For our study, we 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;³ 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.⁴ 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. Excluded from the dataset were courses that students dropped early in the semester (prior to the course census date). Thus, in our study, “course withdrawal” denotes that a student paid full tuition for a course but did not persist to the end of the course. “Course persistence” indicates that students remained in the course through the end of the semester.

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 of the colleges are comprehensive (offering both academic transfer track and occupationally oriented associate degrees), but five are technical colleges that primarily offer occupational degrees. Overall, however, Washington community colleges seem to more closely

³ 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.

⁴ The state board divided courses into three categories: face-to-face, online, and hybrid. Given that less than 2 percent 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 percent 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 through 4.

represent an urban and White student population than do community colleges in the country as a whole.⁵

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 students enrolled in an academic transfer track ($N = 22,624$), who intended to eventually transfer to a four-year school and earn a bachelor's degree. Among these students, 95 percent lived within 65 miles of their home college. An outlying 1 percent lived very far away from the college (≥ 182 miles), with most such addresses lying outside state boundaries. These outliers were excluded from analysis, resulting in a sample size of 21,989.⁶

Because our goal was to understand the impact of course delivery *within* specific courses, we excluded courses where all sections were offered through the same delivery format within a school. All of the courses in our sample 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 were taken at a school that was not the student's primary college. This observation raises the concern that students who lived far from their home college may have enrolled in a closer college for any face-to-face courses; if that were the case, distance would be endogenous. However, in our dataset, students tended to take all

⁵ This description is based on statistics reported to the 2004 Integrated Postsecondary Education Data System database.

⁶ Many of these outliers took a substantial proportion of face-to-face courses at their college. According to the Washington State Board of Community and Technical Colleges, these students likely provided their parents' home address or their own previous address rather than their own address at the time of college entry. Thus, it seemed sensible to exclude them. This observation, however, raises the concern that students remaining in the sample may also have provided incorrect addresses. Although a small proportion of students may indeed have provided incorrect or out-of-date addresses, we suspect the degree of error is minor, given that we found our measure of distance to be significantly and positively related to online course-taking.

courses at their home college; less than 0.003 percent of the courses in the sample were taken at a school that was not the student's home college. To be conservative, we dropped those courses from the analysis to avoid potential selection bias.⁷

The final analysis sample included 124,371 course enrollments among 18,569 students, with approximately 22 percent of the enrollments in online courses. Student summary statistics are displayed in Table 1. 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 of 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.⁸ 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 subject fixed effects to control for student self-selection into different subjects (see section 3.1 for details).

⁷ In a separate robustness check, we included those courses in the analysis, and the results were almost identical to those presented in Tables 1 to 4.

⁸ Although first-term GPA provides a useful sense of students' academic capacity, it could be affected by students' choices of online versus face-to-face formats during their first term. However, less than 13 percent ($N = 2,362$) 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 1
Student Characteristics

Characteristics	Full Student Sample	Ever-Online Student Sample	Never-Online Student Sample	Difference (Ever-Never)
Demographic characteristics				
Female	0.527 (0.499)	0.573 (0.495)	0.477 (0.500)	0.096**
White	0.697 (0.460)	0.709 (0.454)	0.683 (0.465)	0.026**
African American	0.044 (0.205)	0.037 (0.189)	0.051 (0.221)	-0.014**
Hispanic	0.022 (0.148)	0.021 (0.143)	0.024 (0.153)	-0.003
American Indian	0.014 (0.118)	0.012 (0.108)	0.017 (0.129)	-0.005**
Asian	0.075 (0.265)	0.077 (0.267)	0.074 (0.262)	0.003
Alaska Native	0.001 (0.034)	0.001 (0.029)	0.001 (0.038)	0.000
Native Hawaiian	0.004 (0.061)	0.004 (0.060)	0.004 (0.062)	0.000
Pacific Islander	0.002 (0.050)	0.001 (0.035)	0.004 (0.061)	-0.003**
Multiracial	0.041 (0.200)	0.042 (0.200)	0.042 (0.199)	0.000
Unknown race	0.063 (0.242)	0.061 (0.239)	0.064 (0.246)	-0.003
Age	21.298 (6.576)	21.438 (6.630)	21.150 (6.516)	0.288*
Eligible for need-based aid	0.420 (0.494)	0.443 (0.497)	0.396 (0.489)	0.047**
Highest SES	0.176 (0.381)	0.188 (0.391)	0.163 (0.370)	0.025**
Higher SES	0.223 (0.416)	0.229 (0.420)	0.217 (0.412)	0.012*
Middle SES	0.206 (0.405)	0.202 (0.401)	0.211 (0.408)	-0.009
Lower SES	0.181 (0.385)	0.176 (0.381)	0.186 (0.389)	-0.010†
Lowest SES	0.138 (0.344)	0.130 (0.337)	0.145 (0.352)	-0.015**

Table 1, continued

Characteristics	Full Student Sample	Ever-Online Student Sample	Never-Online Student Sample	Difference (Ever-Never)
Unknown SES	0.076 (0.265)	0.075 (0.263)	0.077 (0.267)	-0.002
Average working hours in a term	194.6 (174.1)	202.7 (171.7)	186.0 (176.3)	16.7**
Distance to college (in miles)	16.838 (10.971)	17.125 (11.187)	16.532 (10.728)	0.593**
Academic characteristics				
Took reading/writing dev ed	0.214 (0.410)	0.208 (0.406)	0.227 (0.419)	-0.019**
Took math dev ed	0.634 (0.482)	0.641 (0.480)	0.621 (0.485)	0.02**
Limited English proficiency	0.002 (0.040)	0.002 (0.041)	0.002 (0.039)	0.000
Dual enrolled prior to entry	0.088 (0.284)	0.095 (0.293)	0.081 (0.273)	0.014**
GPA at end of first term ^a	2.891 (0.945)	2.982 (0.872)	2.791 (1.009)	0.191**
Credits at end of first term	11.204 (4.851)	11.636 (4.715)	10.746 (4.951)	0.890**
Average credits taken in a term	12.838 (3.298)	13.031 (3.101)	12.633 (3.4843)	0.398**
Observations	18,569	9,559	9,010	

Note. Dev ed = developmental education.

^a $N = 17,360$ for the full student sample, $N = 9,078$ for the ever-online student sample, and $N = 8,282$ for the never-online student sample.

† $p < .10$. * $p < .05$. ** $p < .01$.

2.3 Online Courses in Washington Community Colleges

Washington represents an excellent context for studying the potential of distance education as an effective replacement for the traditional classroom in community colleges, as the state'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 institution’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, which ranged from 10 percent to 37 percent.

In general, across the five-year period of the study, online course-taking increased substantially in Washington’s community colleges. In the fall of 2004, entering students attempted an average of 1.03 credits online (12 percent of their term credits); by the spring of 2009, still-enrolled students in the 2004 cohort had more than doubled their rate of distance credit attempts to an average of 2.56 credits (39 percent 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 time. Second, among only students who were actively online in a given term, the percentage of credits taken online also increased across terms. These patterns highlight the necessity of controlling for school-level and term-level variation in the current study.

3. Method

3.1 Basic Empirical Model

To assess the effects of online course delivery, we used regression techniques, beginning with a basic OLS model. The key explanatory variable is whether students took each course in an online format or a face-to-face format. 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:

$$Y_{itkj} = \alpha + \beta \text{online}_{itkj} + \gamma X_i + \pi_t + \rho_k + \sigma_j + \mu_{itkj} \quad (1)^9$$

⁹ Given that one of the outcome variables (course persistence) is discrete, we also used logistic regression as a robustness check for this analysis, with results similar to those presented in Table 3.

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, SES), academic preparedness (e.g., remedial status, previous dual enrollment), and semester-level information (e.g., working hours in current term, total credits taken in current term).¹⁰ 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 Course Fixed Effects Approach

By including college, term, and course subject fixed effects, Equation 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 Equation 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 a course fixed effects model in addition to using college, term, and subject fixed effects, thus effectively comparing online and face-to-face sections of the same course.¹¹

¹⁰ 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.

¹¹ Note that academic subject, term, and college fixed effects are automatically dropped when course fixed effects are added to the model, as these are attributes of the course.

3.3 Addressing Within-Course Selection Using an Instrumental Variable Approach

Although 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 Equation 1 to use an IV approach:

$$Y_{itkj} = \alpha + \beta \text{online}_{itkj} + \gamma X_i + \pi_t + \rho_k + \sigma_j + \mu_{itkj} \quad (2)$$

where: $\text{online}_{itkj} = \alpha + \delta \text{distance}_i + \gamma X_i + \pi_t + \rho_k + \sigma_j + \mu_{itkj}$

In Equation 2, the key explanatory variable online_{itkj} is instrumented using distance from the student’s home to the college of attendance. The coefficient β thus represents an unbiased estimate of the impact of course format on course outcomes—but only if distance is indeed an appropriate instrument.

There are four potential concerns about using distance as an instrument in this context. First, researchers (e.g., Long & Kurlaender, 2009) have indicated 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 and excluded outliers living extremely far away from their home college; in our sample, the average distance from a student’s home to the college of attendance was 17 miles, with nearly 90 percent of students 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.

Second, one might be concerned about two potential endogeneity issues related to 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). We have addressed this concern to a certain extent by limiting the sample to students who were enrolled in an academic transfer track (as opposed to a career-technical track) and thus relatively homogeneous in their educational intent. The other potential difficulty with distance as an instrument is that proximity to college might directly affect student course outcomes, rather than merely affecting them indirectly through the online treatment. To address both concerns, we conducted a falsification test 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 the next section.

4. Results

4.1 Ordinary Least Squares Estimates

For the total sample of 124,371 course enrollments, the overall course persistence rate was 93 percent, with a gap between online courses (91 percent) and face-to-face courses (94 percent). For enrollments that persisted until the end of the semester ($N = 116,050$), 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). The left panel in Table 2 presents OLS estimates from Equation 1, which we used to examine the relationship between course format and the outcomes of course persistence and course grade. The baseline regression (specification 1) 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. Specifically, students who took courses through the online format were less likely to persist in the course by 3.6 percentage points. Among students who persisted through the course, the average grade for online courses was approximately 0.19 grade points lower than the average grade for face-to-face courses. When we accounted for differences across colleges, course subjects, and terms with fixed effects (specification 2), the estimated negative relationship became larger for both outcome measures; after course fixed effects were added into the model (specification 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.

Results from the OLS analyses with the full set of fixed effects were consistent with those observed in Virginia community colleges¹² using a multilevel propensity score analysis (Xu & Jaggars, 2011). As with this earlier study, however, the fixed-effects OLS analysis cannot entirely control for unobserved confounding variables. Although using course fixed effects addresses concerns that the distribution of delivery formats across

¹² In the 2011 study by Xu and Jaggars, estimates for both course persistence and course grade showed robust negative relationships with the online format. However, the estimates for those outcomes for the Washington sample are only about one third of the size of the estimates for those outcomes for the Virginia sample. The difference in size is likely due to local factors, perhaps including the fact that courses were considered “online” in Virginia only if 80 percent or more of content was delivered online, whereas in Washington, “online” courses may have had as little as 51 percent of content delivered online.

courses may not be random, these fixed effects are sufficient only if students unsystematically choose their particular sections within a course in a college, conditional on observed covariates. To account for the possibility that additional unobserved characteristics also jointly influenced online course enrollment and course outcomes, we used an IV approach.

Table 2
Estimates of the Effect of Taking a Course Through the Online Format

Outcome	OLS			IV		
	Baseline (1)	Adding Time, College, and Subject FE (2)	Adding Course FE (3)	Baseline (4)	Adding Time, College, and Subject FE (5)	Adding Course FE (6)
Dependent variable: course persistence						
Online format	-0.036* (0.003)	-0.041* (0.003)	-0.044* (0.003)	-0.053* (0.023)	-0.052* (0.024)	-0.060* (0.028)
Observations	124,371	124,371	124,371	124,371	124,371	124,371
Dependent variable: course grade						
Online format	-0.190* (0.018)	-0.228* (0.017)	-0.261* (0.016)	-0.280* (0.135)	-0.303* (0.140)	-0.337* (0.160)
Observations	116,050	116,050	116,050	116,050	94,525	94,525
College and subject FE	No	Yes	Yes	No	Yes	Yes
Year-term FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	No	Yes	No	No	Yes

Note. FE = fixed effects. 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 dummy variable, race dummy variables, socioeconomic status dummy variables, a dummy variable for federal financial aid receipt, a dummy variable for limited English proficiency, a dummy variable for dual enrollment prior to college, the total number of credits taken in that term, a dummy variable for students' enrollment in remedial courses, total working hours in that term, and a dummy variable for full-time college enrollment in that term.

* $p < .05$.

4.2 Instrumental Variable Estimates

To address additional concerns about selection, our IV strategy used the distance between a student's home and college of attendance as an instrument for the likelihood of enrolling in an online rather than face-to-face section of a particular course. Table 3 shows the first-stage results for Equation 2 and indicates that distance from a student's home to the student's college of attendance is a significant and positive predictor of online enrollment across all models. We conducted F -tests on the excluded instrument to test its strength,¹³ and our results indicated that distance does indeed help explain which students choose online course sections, no matter which model specification is employed.

The right panel in Table 2 shows the IV estimates for online learning in terms of each course outcome measure, where each specification used the first-stage estimates with corresponding specifications. 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; the IV estimate controlling for all fixed effects (specification 6) is -0.06 for course persistence, compared with -0.04 based on the OLS model, and -0.33 for course grade, compared with -0.26 based on the OLS model. The magnification of the estimates after controlling for both observed and unobserved characteristics may support 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.

¹³ Stock, Wright, & 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.

Table 3
Results of First-Stage IV Regressions:
Probability of Taking a Course Through the Online Format

Instrumental Variable	Baseline (1)	Adding Time, College, and Subject FE (2)	Adding Course FE (3)
Distance to college	0.003* (0.0002)	0.003* (0.0002)	0.003* (0.0001)
College and subject FE	No	Yes	Yes
Year-term FE	No	Yes	Yes
Course FE	No	No	No
Observations	124,371	124,371	124,371
<i>F</i> -test on excluded instruments	268.22	317.43	280.74
(Prob > <i>F</i>)	< 0.001	< 0.001	< 0.001

Note. FE = fixed effects. Standard errors for all models are clustered at the course level. All models also include the following covariates: gender dummy variable, race dummy variable, socioeconomic status dummy variable, a dummy variable for federal financial aid receipt, a dummy variable for limited English proficiency, a dummy variable for dual enrollment prior to college, the total number of credits taken in that term, and a dummy variable for full-time college enrollment in that term.

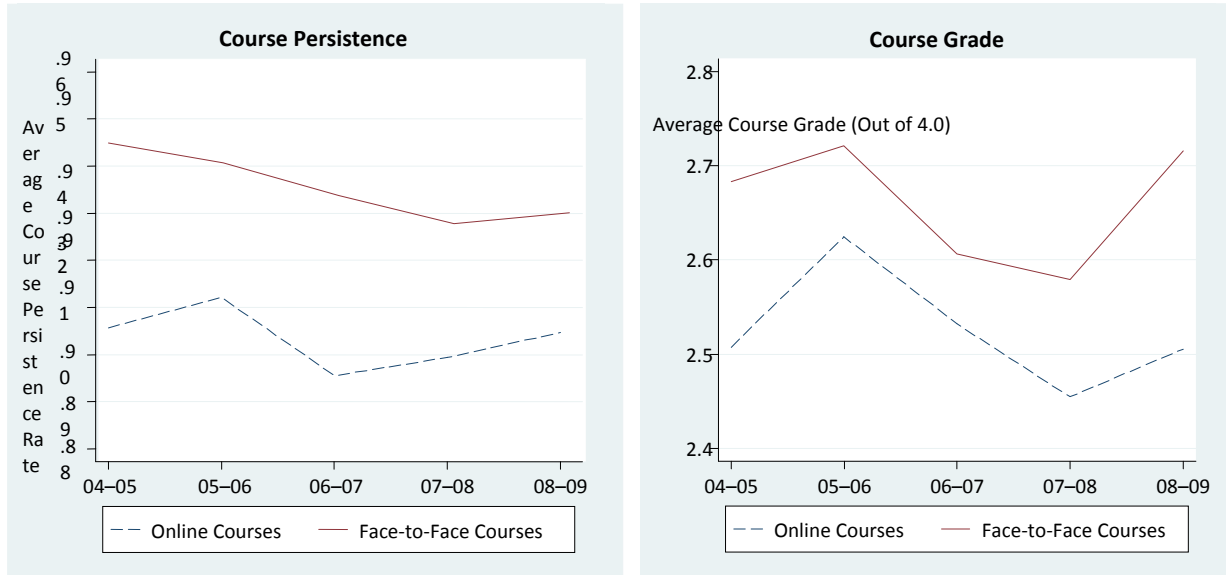
* $p < .05$.

One potential 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 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 Figure 1 suggest that although course outcomes varied over time, the gap in performance between online and face-to-face outcomes remained fairly consistent.

We also conducted a more explicit test of whether the gap remained consistent by estimating a version of specification 6 (IV estimates using course fixed effects) that included interaction terms between year dummies and course format for each course outcome. 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 ($F = 1.25, p = 0.22$) or course grade ($F = 0.23, p = 0.92$). That is, the adjusted association between course format and student performance

did not change significantly over the four-year span of the study, suggesting that evolving technologies either were not adopted or did not have a strong impact on online success.

Figure 1
Course Outcomes by Delivery Format Over Time



4.3 Validity of the Instrumental Variable

The validity of the IV identification strategy used in the current study rests on the assumption that distance is a legitimate instrument for online enrollment. Table 3, which shows the results of the first-stage IV regressions, indicates that distance is significantly and positively related to online enrollment. However, for the IV estimates to be consistent, it must also be the case that distance is uncorrelated with the error term.

There are at least two potential threats to the validity of using distance as an instrument: that those who value education might choose to live closer to a college campus, and that students living closer to campus might perform at a higher level due to easy access to college facilities and instructors. Either scenario would result in a correlation between the instrumental variable and the error term. To assess the extent of this potential problem, we conducted an exploratory analysis in which we excluded all

online courses from the course sample and examined the relationship between course outcomes and distance for the subsample of face-to-face courses.¹⁴ If students living farther from campus were systematically less motivated or encountered greater inconvenience in accessing school resources, then distance would be directly related to course outcomes for this subsample. The results of this exploration (see Table 4), which are robust to all model specifications, suggest that there is 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.

Table 4
OLS Estimates of the Effect of Distance on the Course Outcomes of Face-to-Face Courses

	Baseline (1)	Adding Time, College, and Subject FE (2)	Adding Course FE (3)
Dependent variable: course persistence			
Distance	0.00007 (0.00008)	0.00008 (0.00008)	0.00006 (0.00008)
Observations	97,276	97,276	97,276
Dependent variable: course grade			
Distance	-0.0002 (0.0004)	-0.0003 (0.0004)	-0.0002 (0.0004)
College and subject FE	No	Yes	Yes
Year-term FE	No	Yes	Yes
Course FE	No	No	Yes

Note. FE = fixed effects. All estimates failed to reach statistical significance at the $p < 0.10$ level. Standard errors for all models are clustered at the course level. All models also include the following covariates: gender dummy variable, race dummy variable, socioeconomic status dummy variable, a dummy variable for federal financial aid receipt, a dummy variable for limited English proficiency, a dummy variable for dual enrollment prior to college, the total number of credits taken in that term, and a dummy variable for full-time college enrollment in that term.

¹⁴ Removing online courses from the sample did not substantially curtail our student sample size or variability among the sample in terms of distance from campus; more than 97 percent of students took at least one face-to-face course during their time at college.

4.4 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 2.

Another potential concern was that our results were driven by a small set of individuals who took an entirely online curriculum or a high proportion of courses online. Yet among the 18,569 students in the sample, less than 3 percent ($N = 550$) 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 ($N = 395$) took no more than three online courses before they dropped out from the college. As a result, the courses taken by these students ($N = 1,712$) make up only 1 percent 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 2.

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 percent of enrollments were in face-to-face sections ($N = 119,361$) and reran the analysis on this subsample. Despite minor variations in the coefficients, the results were qualitatively similar to those presented in Table 2.

Finally, given that one of the outcome variables is discrete, and potential analytic problems may derive from using linear regression as the model specification, we used a probit model as a robustness check for the relationship between online format and course persistence. The estimates of the marginal effects based on the probit model did not substantively alter the interpretation of the estimates for course persistence presented in Table 2.

4.5 Generalizability

Because of the IV approach that we used as the empirical strategy to isolate the causal impact of the online delivery format, we chose to limit our sample to Washington State residents who were on an academic transfer track as opposed to a career-technical track (hereafter referred to as the “IV sample”). As a result, our estimates may not generalize to the entire student population in Washington community and technical colleges (hereafter referred to as the “full student sample”). To explore the potential differences between the impact of course format on the full student sample ($N = 177,028$) versus the IV sample, we estimated the non-IV model with course fixed effects for the full student sample¹⁵ and compared it with results based on the same model for the IV sample (specification 3 in Table 2). For course persistence, the estimate based on the full sample is -0.048 ($p < 0.01$), approximately 9 percent larger than the IV sample estimate using the same model specification (-0.044 using model specification 3). For course grade, the full sample estimate is -0.303 ($p < 0.01$), about 16 percent larger than the IV sample estimate (-0.261 using model specification 3). One possible explanation is that the students on the transfer track were more academically motivated and experienced fewer difficulties adjusting to the online learning environment. Another possibility is that career-technical courses were more difficult to translate into the online context, making it more difficult for students in those courses to perform well in the online environment. Although an IV approach cannot be used to isolate the causal impact of course delivery format on the full student sample, these robustness checks suggest that the IV results for the transfer-track students do not overestimate the average effect of online delivery format on community college students.

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

¹⁵ To use course fixed effects, we still limited the sample to courses with both online and face-to-face sections.

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 course fixed effects to address within- and between-course selection. In practical terms, these results indicate that on average, for a given student, taking a particular course in an online rather than face-to-face format would increase his or her likelihood of course withdrawal by 6 percentage points, and if the student persisted to the end of the course, it would lower his or her final grade by more than 0.3 points (e.g., from an A to an A-, or from a B+ to a B).

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 potential direction of this 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.

There are several possible reasons why online courses could be less effective than traditional face-to-face courses in the community college setting. First, community college students are often academically underprepared when they enter college and might thus be more susceptible to technical difficulties in online courses (Frankola, 2001). They may also lack time management and independent learning skills, which are thought to be critical to success in online and distance education (see, e.g., Bambara, Harbour, Davies, & Athey, 2009; Ehrman, 1990; Eisenberg & Dowsett, 1990). In addition, recent studies suggest that students' poor performance in online courses may be in part due to low levels of "teacher presence," or the sense that the instructor is a real person who is supporting and motivating students to learn the material (Bambara, Harbour, Davies, & Athey, 2009; Jaggars, 2012). Moreover, many online instructors simply convert their face-to-face instructional materials to printed handouts and text-heavy PowerPoint presentations, with few of the interactive technologies that may effectively engage students in online learning (Edgecombe, Barragan, & Rucks-Ahidiana, 2013; Cox, 2006).

Despite these issues, online learning is an important strategy to improve course access and flexibility in higher education, especially in community colleges, 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. Finally, in order to maintain or increase enrollments, colleges must be responsive to the needs and demands of their students, and community colleges believe that their students need the flexibility of online learning (Parsad & Lewis, 2008).

Given the value of these benefits, online courses are likely to become an increasingly important feature of postsecondary education. Accordingly, colleges, especially open-access institutions, need to take steps to ensure that students perform as well in online courses as they do in face-to-face courses. In particular, colleges may need to create infrastructures to support both faculty and students (Edgecombe et al., 2013). In terms of faculty support, 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). Yet in community colleges, most faculty are left to design online courses on their own and keenly feel a lack of training and support (Cox, 2006; Millward, 2008; Pagliari, Batts, & McFadden, 2009). In terms of student support, a shift toward online learning would require a rethinking and potential expansion of supports such as tutoring; advising and counseling; library support services; and faculty office hours, which in many colleges are available only on campus and during regular working hours (Compora, 2003; Zavarella, 2008).

Most community college systems, such as that in Washington State, have already expended substantial resources to provide supports for online students and faculty. 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 necessary in order for such supports to have sustained effectiveness (Karp, 2011). Yet creating more in-depth, systematic, and proactive supports for online faculty and students will likely require substantially higher per-course expenditures, potentially eroding the promise of cost savings associated with online course offerings.

Accordingly, there is an urgent need for two strands of future research. First, researchers need to empirically identify high-quality online courses, as well as strategies that contribute to stronger student learning and performance outcomes in an online learning environment. Most prior research in this domain has been based on self-report surveys (e.g., Grandzol & Grandzol, 2006; Keeton, 2004; MacDonald, Stodel, Farres, Breithaupt, & Gabriel, 2001; Ralston-Berg, 2010, 2011; Smissen & Sims, 2002; Young, 2006). More research linking specific aspects of course quality with concrete student-level course outcomes is needed in order to provide direction for colleges that wish to improve their online learning systems. Second, researchers should work to systematically quantify the costs associated with online learning, particularly the costs of high-quality online courses—those that yield student outcomes that are at least equivalent to those of face-to-face courses that cover similar topics with similar student populations. 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.

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.

References

- Adelman C. (2005). *Moving into town—and moving on: The community college in the lives of traditional-age students*. Washington, DC: U.S. Department of Education.
- Alfonso, M. (2006). The impact of community college attendance on baccalaureate attainment. *Research in Higher Education*, 47(8), 873–903.
- Alfonso, M., Bailey, T., & Scott, M. (2005). Educational outcomes of occupational sub-baccalaureate students: Evidence from the 1990s. *Economics of Education Review*, 24(2), 197–212.
- Alvarez, D. M., Blair, K., Monske, E., & Wolf, A. (2005). Team models in online course development: A unit-specific approach. *Journal of Educational Technology & Society*, 8(3), 176–186.
- Bacow, L. S., Bowen, W. G., Guthrie, K. M., Lack, K. A., & Long, M. P. (2012). *Barriers to adoption of online learning systems in U.S. higher education*. New York, NY: ITHAKA S+R.
- Bailey, T., & Morest, V. S. (2006). Introduction. In T. Bailey & V. S. Morest (Eds.), *Defending the community college equity agenda* (pp. 1–27). Baltimore, MD: Johns Hopkins University Press.
- Bambara, C. S., Harbour, C. P., Davies, T. G., & Athey, S. (2009). Delicate engagement: The lived experience of community college students enrolled in high-risk courses. *Community College Review*, 36(3), 219–238.
- Beatty-Guenter, P. (2002, May). *Why distance education? Mimetic forces in institutions of adult education*. Paper presented at the 21st Annual National Conference of the Canadian Association for the Study of Adult Education, Toronto, Ontario.
- Caldwell, E. R. (2006). *A comparative study of three instructional modalities in a computer programming course: Traditional instruction, Web-based instruction, and online instruction* (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses database (UMI No. AAT 3227694).
- Card, D. (1995). Using geographic variation in college proximity to estimate the return to schooling. In L. N. Christofides, E. K. Grant, & R. Swidinsky (Eds.), *Aspects of labor market behavior: Essays in honour of John Vanderkamp*. Toronto, Canada: University of Toronto Press.
- Carr, S. (2000, February 11). As distance education comes of age, the challenge is keeping the students. *The Chronicle of Higher Education*, pp. A39–A41.

- Cavus, N., & Ibrahim, D. (2007). Assessing the success rate of students using a learning management system together with a collaborative tool in Web-based teaching of programming languages. *Journal of Educational Computing Research*, 36(3), 301–321.
- Chambers, T. E. (2002). *Internet course student achievement: In Ohio's two-year community and technical colleges, are online courses less effective than traditional courses?* (Doctoral dissertation). Bowling Green State University, Bowling Green, OH.
- Chen, A. (2012, September 14). Florida ponders opening an online-only public university. *The Chronicle of Higher Education*. Retrieved from <http://chronicle.com/>
- Compora, D. P. (2003). Current trends in distance education: An administrative model. *Online Journal of Distance Learning Administration*, 6(2). Retrieved from <http://www.westga.edu/~distance/ojdl/summer62/compora62.html>
- Cox, R. D. (2006). Virtual access. In T. Bailey & V. S. Morest (Eds.), *Defending the community college equity agenda* (pp. 110–131). Baltimore, MA: Johns Hopkins University Press.
- Edgecombe, N., Barragan, M., & Rucks-Ahidiana, Z. (2013). *Enhancing the online experience through interactive technologies: An empirical analysis of technology usage in community college*. Unpublished manuscript.
- Ehrman, M. (1990). Psychological factors and distance education. *American Journal of Distance Education*, 4(1), 10–24.
- Eisenberg, E., & Dowsett, T. (1990). Student drop-out from a distance education project course: A new method of analysis. *Distance Education*, 11(2), 231–253.
- Figlio, D. N., Rush, M., & Yin, L. (2010). *Is it live or is it Internet? Experimental estimates of the effects of online instruction on student learning* (NBER Working Paper No. 16089). Cambridge, MA: National Bureau of Economic Research.
- Frankola, K. (2001). Why online learners drop out. *Workforce*, 80(10), 53–59.
- Grandzol, J. R., & Grandzol, C. J. (2006). Best practices for online business education. *International Review of Research in Open and Distance Learning*, 7(1). Retrieved from <http://www.irrodl.org/index.php/irrodl/article/view/246/475>
- Hawkes, M., & Cambre, M. (2000). The cost factor: When is interactive distance technology justifiable? *THE Journal*, 28(1), 26–32.
- Hawkes, M., & Coldeway, D. O. (2002). An analysis of team vs. faculty-based online course development: Implications for instructional design. *Quarterly Review of Distance Education*, 3(4), 431–441.

- Hixon, E. (2008). Team-based online course development: A case study of collaboration models. *Online Journal of Distance Learning Administration*, 11(4). Retrieved from <http://www.westga.edu/~distance/ojdla/winter114/hixon114.html>
- Howell, S. L., Laws, R. D., & Lindsay, N. K. (2004). Reevaluating course completion in distance education. *Quarterly Review of Distance Education*, 5(4), 243–252.
- Hyllegard, D., Heping, D., & Hunter, C. (2008). Why do students leave online courses? Attrition in community college distance learning courses. *International Journal of Instructional Media*, 35(4), 429–434.
- Jaggars, S. S., & Bailey, T. (2010). *Effectiveness of fully online courses for college students: Response to a Department of Education meta-analysis*. New York, NY: Columbia University, Teachers College, Community College Research Center.
- Jewett, F. I. (2000). A model for comparing the costs of using distance instruction and classroom instruction. *American Journal of Distance Education*, 14(2), 37–47.
- Jung, I. (2003). Cost-effectiveness of online education. In M. G. Moore & W. G. Anderson (Eds.), *Handbook of distance education* (pp. 717–726). Mahwah, NJ: Lawrence Erlbaum Associates.
- Karp, M. M. (2011). *Toward a new understanding of non-academic student support: Four mechanisms encouraging positive student outcomes in the community college* (CCRC Working Paper No. 28, Assessment of Evidence Series). New York, NY: Columbia University, Teachers College, Community College Research Center.
- Keeton, M. T. (2004). Best online instructional practices: Report of phase I of an ongoing study. *Journal of Asynchronous Learning Networks*, 8(2). Retrieved from <http://sloanconsortium.org/jaln/v8n2/best-online-instructional-practices-report-phase-i-ongoing-study>
- Knowles, E., & Kalata, K. (2007). A model for enhancing online course development. *Innovate*, 4(2). Retrieved from http://www.innovateonline.info/pdf/vol4_issue2/A_Model_for_Enhancing_Online_Course_Development.pdf
- LaRose, R., Gregg, J., & Eastin, M. (1998). Audiographic telecourses for the Web: An experiment. *Journal of Computer-Mediated Communication*, 4(2). Retrieved from <http://jcmc.indiana.edu/vol4/issue2/larose.html>
- Levine, A., & Sun, J. (2002). *Barriers to distance education. Distributed education: challenges, choices, and a new environment, sixth in a series*. Washington, DC: American Council on Education.
- Long, B. T., & Kurlaender, M. (2009). Do community colleges provide a viable pathway to a baccalaureate degree? *Educational Evaluation and Policy Analysis*, 31(1), 30–53.

- MacDonald, C. J., Stodel, E. J., Farres, L. G., Breithaupt, K., & Gabriel, M. A. (2001). The demand-driven learning model: A framework for Web-based learning. *The Internet and Higher Education*, 4(1), 9–30.
- Mentzer, G. A., Cryan, J., & Teclehaimanot, B. (2007). Two peas in a pod? A comparison of face-to-face and Web-based classrooms. *Journal of Technology and Teacher Education*, 15(2), 233–46.
- Millward, J. (2008). An analysis of the national “TYCA Research Initiative Survey Section III: Technology and Pedagogy” in two-year college English programs. *Teaching English in the Two-Year College*, 35(4), 372–398.
- Moore, K., Bartkovich, J., Fetzner, M., & Ison, S. (2003). Success in cyberspace: Student retention in online courses. *Journal of Applied Research in the Community College*, 10(2), 107–118.
- Odell, M., Abbitt, J., Amos, D., & Davis, J. (1999). Developing online courses: A comparison of Web-based instruction with traditional instruction. In J. Price et al. (Eds.), *Proceedings of Society for Information Technology & Teacher Education International Conference 1999* (pp. 126–130). Chesapeake, VA: Association for the Advancement of Computing in Education.
- Pagliari, L., Batts, D., & McFadden, C. (2009). Desired versus actual training for online instructors in community colleges. *Online Journal of Distance Learning Administration*, 12(4). Retrieved from <http://www.westga.edu/~distance/ojdl/winter124/pagliari124.html>
- Parsad, B., & Lewis, L. (2008). *Distance education at degree-granting postsecondary institutions: 2006–07* (Report No. NCES 2009-044). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics.
- Peterson, C. L., & Bond, N. (2004). Online compared to face-to-face teacher preparation for learning standards-based planning skills. *Journal of Research on Technology in Education*, 36(4), 345–360.
- Planty, M., Hussar, W., Snyder, T., Kena, G., KewalRamani, A., Kemp, J., Bianco, K., & Dinkes, R. (2009). *The condition of education 2009* (Report No. NCES 2009-081). Washington, DC: U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics.
- Puzziferro, M., & Shelton, K. (2008). A model for developing high-quality online courses: Integrating a systems approach with learning theory. *Journal of Asynchronous Learning Networks*, 12(3–4), 119–136.
- Ralston-Berg, P. (2010, June). *Do quality standards matter to students?* Paper presented at the 2nd Annual Quality Matters Conference, Oak Brook, IL.

- Ralston-Berg, P. (2011, November). *What makes a quality online course? The student perspective*. Paper presented at the 3rd Annual Quality Matters Conference, Baltimore, MD.
- Rogers, B. (2001). *Analysis of funding issues related to distance learning in the North Carolina Community College System*. Retrieved from <http://www.nccommunitycolleges.edu/Reports/docs/LegislativeReports/funding.pdf>
- Rouse, C. E. (1995). Democratization or diversion? The effect of community colleges on educational attainment. *Journal of Business Economics and Statistics*, 13(2), 217–224.
- Rumble, G. (2003). Modeling the costs and economics of distance education. In M. G. Moore & W. G. Anderson (Eds.), *Handbook of distance education* (pp. 703–716). Mahwah, NJ: Lawrence Erlbaum Associates.
- Schiffman, S. (2005). Business issues in online education. In J. Bourne & J. C. Moore (Eds.), *Elements of quality education: Engaging communities* (pp. 151–172). Needham, MA: Sloan Consortium.
- Schoenfeld-Tacher, R., McConnell, S., & Graham, M. (2001). Do no harm—A comparison of the effects of on-line vs. traditional delivery media on a science course. *Journal of Science Education and Technology*, 10(3), 257–265.
- Smissen, I., & Sims, R. (2002). *Requirements for online teaching and learning at Deakin University: A case study*. Retrieved from <http://dro.deakin.edu.au/view/DU:30013885>
- Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of the American Statistical Association*, 20(4), 518–529.
- Texas Higher Education Coordinating Board. (2011). *Summary of higher education legislation: 82nd Texas Legislature*. Austin, TX: Author.
- Thille, C. (2008). Building open learning as a community-based research activity. In T. Iiyoshi & M. S. V. Kumar (Eds.), *Opening up education: The collective advancement of education through open technology, open content, and open knowledge* (pp. 165–180). Cambridge, MA: MIT Press.
- Virginia Community College System, Distance Learning Taskforce. (2001). *Virginia Community College System organizational strategy for distance learning: Final report*. Richmond, VA: Virginia Community College System.
- Whalen, T., & Wright, D. (1999). Methodology for cost-benefit analysis of Web-based tele-learning: Case study of the Bell Online Institute. *American Journal of Distance Education*, 13(1), 23–44.

- Xu, D., & Jaggars, S. S. (2011). The effectiveness of distance education across Virginia's community colleges: Evidence from introductory college-level math and English courses. *Educational Evaluation and Policy Analysis*, 33(3), 360–377
- Xu, H., & Morris, L. V. (2007). Collaborative course development for online courses. *Innovative Higher Education*, 32(1), 35–47.
- Young, S. (2006). Student views of effective online teaching in higher education. *American Journal of Distance Education*, 20(2), 65–77
- Zavarella, C. A. (2008). *Computer-based instruction and remedial mathematics: A study of student retention at a Florida community college* (Doctoral dissertation). University of South Florida, Tampa, FL.