Performance Gaps between Online and Face-to-Face Courses: Differences across Types of Students and Academic Subject Areas

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Using a dataset containing nearly 500,000 courses taken by over 40,000 community and technical college students in Washington State, this study examines the performance gap between online and face-to-face courses and how the size of that gap differs across student subgroups and academic subject areas. While all types of students in the study suffered decrements in performance in online courses, those with the strongest declines were males, younger students, Black students, and students with lower grade point averages. Online performance gaps were also wider in some academic subject areas than others. After controlling for individual and peer effects, the social sciences and the applied professions (e.g., business, law, and nursing) showed the strongest online performance gaps.

One of the most pronounced trends in higher education over the last decade has been a strong growth in distance education through online coursework (Allen & Seaman, 2010). While the rise of online distance education has expanded learning opportunities for all students, it is often most attractive to nontraditional students, who are more likely to have employment and family obligations that make attending traditional face-to-face classes difficult (Aslanian, 2001). Perhaps as a consequence, online learning enrollments have increased particularly quickly at community colleges (Choy, 2002; Parsad & Lewis, 2008), where a large proportion of the population are nontraditional students (Kleinman & Entin, 2002).

Di Xu is the Quantitative Research Associate of the Community College Research Center at Teachers College, Columbia University; dx2108@columbia.edu. Shanna S. Jaggars is the Assistant Director of the Commuity College Research Center at Teachers College, Columbia University; jaggars@tc.edu.

While small-scale studies of online learning in elite universities have found few differences in outcomes between online and face-to-face courses (Bailey & Jaggars, 2010), community colleges often observe markedly lower persistence rates and course grades in online courses (e.g., Beatty-Guenter, 2003; Carr, 2000; Chambers, 2002; Cox, 2006; Kaupp, 2012; Moore, Bartkovich, Fetzner, & Ison, 2003). Large-scale studies of two community college systems suggest that these gaps remain even after controlling for student and course characteristics (Xu & Jaggars, 2011; Xu & Jaggars, 2013).

Online learning has the potential to be a democratizing force in higher education; however, to meet this potential, it must not only improve *access* to college courses among traditionally-underserved students, but it must also support the academic *success* of these students. In this article, we examine the gap between online and face-to-face course success rates among community college students, and investigate whether that gap varies according to ethnicity, gender, age, level of academic preparation, and area of study.

Why Some Students May Struggle Online

The literature on online learning suggests that online courses require students to assume greater responsibility for their learning; thus, a successful online student may need high levels of self-regulation, self-discipline, and a related suite of metacognitive skills, which often fall under the broad rubric of self-directed learning (Azevedo, Cromley, & Seibert, 2004; Corbeil, 2003; Guglielmino & Guglielmino, 2002; Hannafin & Land, 1997; Kearsley, 2002; Moore, 1987; Williams, 1996; Yen & Liu, 2009). For example, in a survey of college leaders, a majority agreed with the statement that "students need more discipline to succeed in an online course than in a face-to-face course" (Allen & Seaman, 2005). Students also agree that online courses require more personal responsibility and motivation, as well as greater time management skills, than do face-to-face courses (Bork & Rucks-Ahidiana, 2013; Public Agenda, 2013). And, indeed, the students most likely to select online coursework seem to have higher levels of academic ability and motivation in comparison to peers who select a fully face-to-face course schedule (Brown & Liedholm, 2002; Coates, Humphreys, Kane, & Vachris, 2004; Rovai, Ponton, Wighting, & Baker, 2007; Xu & Jaggars, 2011; Xu & Jaggars, 2013).

However, not all online students have strong self-directed learning skills and, thus, may need additional support or scaffolding in order to build those skills (Azevedo, 2005; Azevedo et al., 2004; Quintana,

Zhang, & Krajcik, 2005; Shapiro, 2000). It is not clear whether most online courses incorporate such scaffolding. However, a recent qualitative study at two community colleges (Bork & Rucks-Ahidiana, 2013) found that many faculty expected their online students to arrive in the course with a preexisting set of self-directed learning skills and did not believe that faculty should be responsible for helping students develop these skills. Other qualitative studies have found that students in online courses experience higher levels of dissatisfaction, interpersonal isolation, feelings of unclear direction and uncertainty, and a lack of engagement in the learning process (Bambara, Harbour, & Davies, 2009; Carr, 2000; Hana & Kling, 1999; Jaggars, 2014). These studies suggest that the typical online course is not explicitly designed to help students develop the skills they need to succeed in this new context. Accordingly, some students may struggle to perform as well in an online course as they would in a similar face-to-face course (Xu & Jaggars, 2011; Xu & Jaggars, 2013).

Variation Across Students

Students' level of self-directed learning may vary according to gender, age, ethnicity, and education level. Studies of adolescents and young adults show that females, White students, and individuals with higher prior educational attainment tend to be more self-directed (e.g. Derrick, Rovai, Ponton, Confessore, & Carr, 2007; Dieber, 1994; Long & Morris, 1996; Reio & Davis, 2005). Self-directed learning skills may also increase with age, before leveling out in the 50s (Long, 2000; Long & Morris, 1996; Merriam & Caffarella, 1999; Reio, 2004; Reio & Davis, 2005).

Given the link between self-directed learning and online success, men, younger students, and ethnic minority students may need additional supports and scaffolding in order to perform as well in an online course as they would in a face-to-face course. In general, these populations perform more poorly in online courses than do their peers (e.g., Chyung, 2001; Colorado & Eberle, 2010; Didia & Hasnat, 1998; Dille & Mezack, 1991; Gunn, McSporran, Macleod, & French, 2003; Newell, 2007; Price, 2006; Rovai & Baker, 2005; Sullivan, 2001; Taplin & Jegede, 2001; Willis, 1992; Wojciechowski & Palmer, 2005). However, it is unclear whether these findings reflect generalized academic difficulties in *any* type of course, a stronger degree of difficulty in adapting to *online* courses in particular, or both.

Only four studies examining the difference between online and face-to-face course performance have considered how this difference may vary across types of students. Two quasi-experimental analyses of uni-

versity economics courses found that online students performed more poorly than face-to-face students. In one study, this decrement in performance seemed more pronounced among men (Brown & Liedholm, 2002), and, in the second, it seemed more pronounced among underclassmen, students with financial aid, and those who didn't consider themselves good at math (Coates, Humphreys, Kane, & Vachris, 2004). An experimental study of another university economics course found no difference between online and face-to-face outcomes among White students, females, or those with higher prior GPAs; however, Hispanic students, males, and those with lower prior GPAs performed more poorly in the online than in the face-to-face course section (Figlio, Rush, & Yin, 2010).

Finally, a descriptive study using California community college student transcripts (Kaupp, 2012) found that both White and Hispanic students performed more poorly in online courses than they did in face-to-face courses, with the effect being stronger among Hispanic students. Accordingly, the performance gap between White and Hispanic students in face-to-face courses (approximately one-quarter of a grade point) was exacerbated in online courses (increasing to over one-third of a grade point). Kaupp (2012) points out that in addition to individual differences in skills such as self-directed learning, some community college student populations may struggle in online courses due to inequities in computer and Internet access (Gladieux & Swail, 1999). For example, in 2011, only 57% of African American and 58% of Hispanic households had high-speed Internet access at home, compared to 76% of White and 83% of Asian households (National Telecommunications, 2013).

Variation Across Courses

Regardless of students' individual characteristics, the challenge of an online course (vis-à-vis a face-to-face course) may be stronger in some subject areas than in others. For example, it may be more difficult to create effective online materials, activities, or assignments in fields that require a high degree of hands-on demonstration and practice, intensive instructor-student interaction, or immediate personalized feedback (Kearsley, 2002). In a recent qualitative study of community college students enrolled in online courses, students explicitly identified some subject areas that they felt were "poorly suited to online learning" (Jaggars, 2014, p. 32), particularly laboratory science courses and foreign language courses. However, no empirical research has yet examined variation across subject areas in terms of how well students perform online versus face-to-face.

Examining Gaps Across Students and Course Subjects

In order to support student success, particularly among traditionally underserved students, community colleges may wish to market online courses more aggressively to students who are likely to benefit from them while devising support systems for students who are likely to experience difficulties with them. Better identifying course subjects that are more- or less-well-suited to online learning may also help institutions approach online course development and expansion more strategically.

To investigate these issues, we took advantage of a large administrative dataset including nearly 500,000 online and face-to-face courses taken by more than 40,000 degree-seeking students who initially enrolled in one of Washington State's 34 community or technical colleges during the fall term of 2004.[1] Following each student for five academic years (to the spring of 2009) allowed us to employ an individual fixed effects approach to assess the impact of online versus face-to-face course delivery on course persistence and course grade.

Course persistence and grade are fundamental measures of success for community college students. Students who withdraw from a course mid-semester run the very real risk of never returning to successfully complete the course, thereby prohibiting progression to the next course in the sequence (see, e.g., Bailey, Jeong, & Cho, 2010). Moreover, many community college students have low incomes (Adelman, 2005) and can ill-afford to pay full tuition for a course that they do not successfully complete.

The results show that all types of students performed more poorly in online courses than they did in face-to-face courses (hereafter, we use the term *online performance gap* to refer to this difference). Males, younger students, Black students, and students with lower prior GPAs had wider online performance gaps than their peers. Moreover, when student subgroups differed in terms of their face-to-face course outcomes (e.g.,White students outperformed ethnic minority students), these differences tended to be exacerbated in online courses.

Empirical Framework and Data

Data and Summary Statistics

Primary analyses were performed on a dataset containing 51,017 degree-seeking students who initially enrolled[2] in one of Washington State's 34 community or technical colleges during the fall term of 2004. These first-time college students were tracked through the spring of

2009 for 19 quarters[3] of enrollment, or nearly five full academic years. The dataset, provided by the Washington State Board of Community and Technical Colleges (SBCTC), included information on student demographics, institutions attended, and transcript data on course enrollments and performance.

In terms of demographics, the dataset provided information on each student's gender, ethnicity (Asian, Black, Hispanic, White, or Other), age (25 or older at college entry), and a variety of other characteristics, including socioeconomic quintile of the census area[4] in which the student lived (hereafter referred to as SES), academic background variables (e.g., whether the student was previously dual-enrolled as a high school student), and other academic metrics that we could calculate from the transcript data (e.g., whether the student ever took a remedial course, hereafter termed *ever-remedial* status; credits enrolled in a given term). The dataset also included information from Washington State Unemployment Insurance (UI) wage records, including individual employment status and working hours for each term.

The transcript data included information on each course, such as course number, course subject,[5] course delivery format,[6] and final grade earned in the course (ranging from a failing grade of 0.0 to an excellent grade of 4.0, including decimals such as 3.4). In addition to course grade, we also used course persistence as an indicator of student performance. The transcript data available to us excluded courses that were dropped early in the semester (prior to the course census date). Thus, the variable *course persistence* is equal to 1 if the given student remained enrolled in the course until the end of the semester, and equal to 0 if the student persisted in the course past the census date (and, therefore, paid full tuition for the course) but did not persist to the end of the semester. The final analysis sample included 498,613 courses taken by 41,194 students (see Table 1 for sample summary statistics).

Empirical Models

To explore whether online delivery has an impact on course persistence and final grade, we began with an ordinary least squares (OLS) model:

$$Y_{its} = \alpha_{its} + \beta \, online_{its} + \gamma \, X_{it} + \pi_t + \rho_s + \overline{p}_c + \mu_{its} \qquad (1)^7$$

where *online* is the key explanatory variable and is equal to 1 if the course was taken online; X_{it} includes demographic attributes (e.g., age, gender, race, SES), academic preparedness (e.g., ever-remedial status, previous dual enrollment), and semester-level information (total credits

TABLE 1

Summary Statistics

	Full Student Sample	Students During the Initial Term
I. Student-Level Characteristics		
Female	0.543 (0.498)	0.538 (0.499)
White	0.691 (0.462)	0.702 (0.458)
African American	0.045 (0.207)	0.044 (0.205)
Hispanic	0.026 (0.160)	0.025 (0.157)
Asian	0.074 (0.261)	0.070 (0.263)
Other Race	0.164 (0.370)	0.155 (0.362)
Age	24.783 (10.002)	23.203 (8.776)
Eligible for Need-Based Aid	0.398 (0.490)	0.469 (0.499)
Highest SES	0.151 (0.358)	0.149 (0.356)
Higher SES	0.202 (0.402)	0.204 (0.403)
Middle SES	0.196 (0.397)	0.201 (0.401)
Lower SES	0.179 (0.383)	0.184 (0.388)
Lowest SES	0.15 (0.357)	0.157 (0.364)
Unknown SES	0.122 (0.327)	0.104 (0.306)
Took Developmental Ed.	0.485 (0.500)	0.552 (0.497)
Limited English Proficiency	0.008 (0.089)	0.003 (0.050)
Transfer-Oriented Program	0.536 (0.499)	0.591 (0.492)
Dual Enrolled Prior to Entry	0.054 (0.227)	0.063 (0.244)
Observations	41,194	31,347
II. Course-Level Characteristics and Outcomes		
Online Delivery Format	0.102 (0.302)	0.055 (0.228)
Number of Credits Taken That Term	14.614 (7.826)	16.105 (7.516)
Hours Worked Per Term††	278.137 (165.002)	257.868 (166.378)
Course Persistence	0.941 (0.235)	0.943 (0.231)
Standardized Course Grade†††	2.59e-09 (0.960)	0.038 (0.964)
Observations	498,613	65,467

† Standard deviations are in parentheses.
†† $N = 297{,}767$ for the full student sample; $N = 37{,}324$ for the initial term.
††† $N = 469{,}287$ for the full student sample; $N = 61{,}765$ for the initial term.

taken in this term). Given that the probability of online enrollment may differ across course subject areas and terms, the model also includes term fixed effects (π_t) and academic subject fixed effects (ρ_s).

While the term ρ_s controls for differences *across* subject areas (such as instructional quality or grading standards), it cannot control for differences across courses *within* a particular subject area. For example, a grade of 3.5 in an introductory course may have a quite different meaning compared to a similar grade in an advanced course. To deal with potential between-course variation in grading standards, we converted each course grade into a standardized *z*-score, based on the typical grades awarded for that particular course. Thus a student's standardized grade in a particular course (for example, History 101) represents how much higher or lower the student's grade was compared to other History 101 students, in standard deviation units.[8] To deal with course-level variation in instructional quality and support that might affect student persistence, we also added a course-level variable to Equation 1 ($\overline{p}_c$) which captured the average persistence rate of the given course.

Equation 1 controls for observed student characteristics, but cannot account for unobservables that may underlie an individual student's propensity to choose online coursework. To deal with this issue, we took advantage of the panel data structure and employed an individual fixed effects approach. Letting *i* denote the individual student and *c* each course, the individual fixed model is written as:

$$Y_{ic} = \alpha_{ic} + \beta \, online_{ic} + \gamma \, X_{ic} + \sigma_i + \upsilon_{ic} \tag{2}$$

The unobserved student characteristics affecting the dependent variable (μ_{its} in Equation 1) are decomposed into two parts in Equation 2: those that are constant, such as fixed personality characteristics (σ_i), and those that vary, such as a student's self-perceived efficacy in a given course subject (υ_{ic}). Averaging this equation over courses for each individual *i* yields:

$$\overline{Y}_i = \overline{\alpha}_i + \beta \, \overline{online}_i + \gamma \, \overline{X}_i + \sigma_i + \overline{\upsilon}_i \tag{3}$$

where $\overline{Y}_i = C^{-1}\Sigma Y_{ic}$, and so on. Because σ_i is fixed across courses, it appears in both Equation 2 and Equation 3. Subtracting (3) from (2) for each course yields:

$$\ddot{Y}_{ic} = \ddot{\alpha}_{ic} + \beta \, online_{ic} + \gamma \, \ddot{X}_{ic} + \ddot{\upsilon}_{ic} \tag{4}$$

where $\ddot{Y}_{ic} = Y_{ic} - \overline{Y}_i$ is the course-demeaned data on course outcome Y, and so on. Further adding time fixed effects (π_t), subject fixed effects

(ρ_s), and the average persistence rate for a given course ($\bar{p}_c$) for models measuring course persistence yields a final individual fixed effects model as follows:

$$\ddot{Y}_{itsc} = \ddot{\alpha}_{itsc} + \beta \; on\ddot{l}ine_{itsc} + \gamma \; \ddot{X}_{itsc} + \pi_t + \rho_s + \bar{p}_c + \ddot{\upsilon}_{itsc} \tag{5}$$

The important thing about Equation 5 is that through the within-individual transformation, the individual-level unobserved effect σ_i has disappeared. In other words, any potential unobserved bias is eliminated through the individual fixed effects model if such bias is constant across courses.[9] Importantly, the model is now effectively comparing between online and face-to-face courses *taken by the same student.* Accordingly, the online coefficient β now explicitly represents the within-student online performance gap.

While an individual fixed-effects model can control for differences between students that may affect their overall propensity to select online courses, it cannot control for time-varying or course-varying individual differences that may prompt a student to select an online section of a particular course. We may have removed some of this variation through the inclusion of term and subject area fixed effects, as well as the time-varying covariate of credits enrolled, and may have further ameliorated its effects by standardizing the dependent variable within courses. To further investigate whether the remaining time-varying individual differences may have biased our results, we also conducted a set of additional robustness checks.

First, students who take multiple online courses may perform more strongly in later online courses than in their first online courses. To address this issue, we added into the individual fixed effects model an indicator of whether the student had previously taken an online course (see Table 3, Model 3). Second, students' level of employment may fluctuate across time, and could directly influence both course-taking patterns and course outcomes. The dataset included quarterly employment information for 60% of the course sample. In an additional robustness check, we added individual working hours in each quarter to the individual fixed effects model as a covariate (see Table 3, Model 4).

Third, while grade standardization should smooth differences in performance between introductory and advanced courses, the level of the course could still influence students' choice to take the course online or face-to-face. For example, advanced courses may be more or less likely to be offered online. To limit the sample to introductory courses, we conducted an additional analysis using only courses taken during the student's first term (see Table 3, Model 5 and 6). Focusing on courses

taken during a student's initial term also helped address a second concern: that students may sort between course modalities based on their previous experience with online learning. Such selection bias may be reduced during the first term, as students do not yet have experience with online courses at the college, nor a strong basis on which to judge their own potential performance in these courses.

Empirical Results

Online Course Enrollments Across Different Subjects

Across the 498,613 course enrollments in the sample, approximately 10% were taken online; however, there was strong variation across subjects in terms of the proportion of online course enrollments. Table 2 presents enrollment patterns in all subject areas, where subject areas are sorted by proportion of online enrollments (from the highest to the lowest). Among the 14 subject-area categories examined, online courses were most popular in the humanities, social science, education, and computer science. In contrast, online enrollments were extremely low in engineering, as well as in the "precollege" courses of developmental education and English as a second language.

Overall Online Performance Gaps

In descriptive terms, students' average persistence rate across courses was 94.12%, with a noticeable gap between online courses (91.17%) and face-to-face courses (94.45%). For courses in which students persisted through to the end of the term ($N = 469{,}287$), the average grade was 2.95 (on a 4.0-point scale), with a gap between online courses (2.77) and face-to-face courses (2.97). For face-to-face courses, the average standardized grade was 0.006, while for online courses, it was –0.054. That is, students typically received lower grades in online sections compared to face-to-face sections of the same course. Table 3 presents the online coefficients for both course persistence and standardized course grade. The left side of the table includes courses taken during any term. The estimates were consistently significant and negative across all model specifications on both course persistence and standardized course grade, indicating that the typical student performed more poorly in online courses than he or she did in face-to-face courses.

Moreover, the negative estimates based on the individual fixed effects model (Model 2), which accounted for unobserved individual characteristics, were approximately 40% larger than those based on the OLS model; adding students' previous online learning experiences (Model 3)

TABLE 2

Proportion of Online Enrollments by Academic Subject Area

Subject Area	Proportion of Enrollments Online	Total Enrollments
Humanities	19.40%	16,787
History	19.32%	10,914
Cultural Studies	16.94%	1,299
Other	20.27%	4,574
Social Science	18.29%	60,161
Geography	22.24%	2,882
Economics	21.40%	7,015
Psychology	18.71%	18,557
Philosophy	18.13%	7,463
Sociology	17.70%	10,991
Anthropology	16.94%	5,562
Political Science	13.95%	4,186
Other	16.06%	3,505
Education	15.15%	7,117
Computer Science	14.99%	23,697
Applied Professions	12.89%	76,244
Business	16.83%	32,879
Law	11.29%	2,800
Nursing and Medical Assistance	9.80%	40,565
English	11.58%	53,880
Mass Communication	10.63%	4,957
Natural Science	8.42%	53,259
Agriculture	1.10%	5,348
Biology	7.14%	23,128
Chemistry	3.71%	11,292
Astronomy	33.39%	3,869
Geology	19.31%	4,568
Physics	2.27%	3,964
Other	4.77%	1,090
Health & Physical Education	8.11%	26,820
Math	6.61%	28,451
Applied Knowledge	5.64%	73,815
Home Making & Family Living	14.93%	4,059
Emergency Management	8.45%	6,690
Art & Design	7.42%	32,166
Mechanics	0.05%	10,959
Masonry	0%	1,765
Other	3.28%	18,176
Foreign Language and Literature	4.81%	12,596
Developmental Education & ESL	3.85%	48,592
Engineering	0.89%	12,237
Total	10.18%	498,613

Note. Please refer to endnote 5 for information on how the subject areas were classified.

and current working hours (Model 4)[10] into the model yielded similar or even larger estimates. These patterns strengthen the notion that students who select online courses have unobserved characteristics that tend to relate to stronger academic performance. As a result, straightforward OLS estimates may tend to underestimate the negative impacts of online course enrollment.

On the right side of Table 3, the sample is limited to only courses taken in a student's initial term. The size and significance of the negative estimates remain consistent for both course outcomes.

Variation in Online Performance Gaps Across Types of Students

In order to explore whether the online performance gap is wider or narrower for certain student subgroups, we examined the potential moderating effects of gender, age, previous academic performance, and ethnicity. The results are presented in Table 4.[11] As a first step in each heterogeneity analysis, we included an overall interaction term between the given individual attribute and course format into Equation 5. To better understand the meaning of each interaction, we then conducted separate analyses on each subgroup using the same model specification.

Overall, every student subgroup showed negative coefficients for online learning in terms of both outcomes; however, the size of the negative estimate varied across type of student. In terms of gender, men had stronger negative estimates compared to women in terms of both course persistence and standardized course grade, though the interaction term was not significant for standardized course grade. In face-to-face courses, women in our sample slightly outperformed men (0.95 vs. 0.94 for course persistence, and 0.079 vs. –0.073 for standardized course grade); the positive interaction term for persistence indicates that the gender gap in persistence was further enlarged in online courses, by approximately 1.4 points.

For students of different ethnicities, all ethnic groups were less likely to persist in an online course than in a face-to-face course, but the size of this difference did not vary across ethnic groups (according to the nonsignificant joint test). In contrast, when we turn to standardized grades among those who persisted in the course, the ethnicities strongly differed in their coefficients for online learning. For example, Black students had more than twice the negative coefficient of Asian students (–0.230 vs. –0.097). In general, Black students already performed more poorly than Asian students in face-to-face courses (0.93 vs. 0.95 for course persistence; –0.308 vs. 0.039 for standardized course grade), and this difference widened in online courses.

TABLE 3
Online versus Face-to-Face Performance Gaps Overall

	Full Course Sample				Initial Semester Only	
	OLS (1)	Individual FE (2)	Adding Previous Online Experiences (3)	Adding Term Working Hours (4)	OLS (5)	Individual FE (6)
Course Persistence						
Coefficient	−0.025***	−0.034***	−0.034***	−0.037***	−0.028***	−0.053***
(*SE*)	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.009)
Individual FE	No	Yes	Yes	Yes	No	Yes
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	498,613	498,613	498,613	297,767	65,467	65,467
Standardized Course Grade						
Coefficient	−0.093***	−0.135***	−0.135***	−0.148***	−0.159***	−0.156***
(*SE*)	(0.005)	(0.006)	(0.006)	(0.008)	(0.020)	(0.027)
Individual FE	No	Yes	Yes	Yes	No	Yes
Subject FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,287	469,287	469,287	279,073	61,765	61,765

Note. Standard errors for all the models are clustered at the student level. All the models also include the following covariates: gender dummy variable, race dummy variable, socioeconomic status dummy variable, a dummy variable for receiving federal financial aid, limited English proficiency variable, 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, a dummy variable for full-time college enrollment in that term, term fixed effects, and academic subject area fixed effects. Models on course persistence also include a control for the average persistence rate in that course.

***Significant at the 1% level.

TABLE 4

Individual Fixed-Effects Estimates for Online Performance Gaps, by Student Subgroup

	Course Persistence	Standardized Course Grade
Gender		
Full-sample estimates		
Online Format (Male)	−0.043 (0.003)***	−0.143 (0.010)***
Female*Online	0.014 (0.004)***	0.012 (0.013)
Subsample estimates		
Female ($N = 272,838$)	−0.029 (0.002)***	−0.126 (0.008)***
Male ($N = 225,775$)	−0.043 (0.003)***	−0.149 (0.010)***
Race		
Full-sample estimates		
Online Format (White)	−0.033 (0.002)***	−0.141 (0.007)***
Black*Online	−0.019 (0.011)*	−0.112 (0.040)***
Hispanic*Online	−0.012 (0.011)	−0.017 (0.044)
Asian*Online	0.005 (0.006)	0.046 (0.023)**
Other Race*Online	−0.003 (0.005)	0.039 (0.017)**
Joint Interaction p-value	0.300	< .001
Subsample estimates		
White ($N = 349,765$)	−0.034 (0.002)***	−0.141 (0.007)***
Black ($N = 19,067$)	−0.051 (0.011)***	−0.230 (0.039)***
Hispanic ($N = 13,687$)	−0.042 (0.011)***	−0.143 (0.043)***
Asian ($N = 42,841$)	−0.027 (0.006)***	−0.097 (0.021)***
Other ($N = 73,253$)	−0.037 (0.004)***	−0.104 (0.016)***
Age (in Fall 2004)		
Full-sample estimates		
Online Format (Younger)	−0.039 (0.002)***	−0.158 (0.007)***
Older*Online	0.018 (0.004)***	0.093 (0.014)***
Subsample estimates		
Older ($N = 122,165$)	−0.021 (0.003)***	−0.059 (0.012)***
Younger ($N = 376,448$)	−0.039 (0.002)***	−0.166 (0.007)***
Remediation Status		
Full-sample estimates		
Online Format (Ever-Remedial)	−0.036 (0.003)***	−0.142 (0.008)***
Non Remedial*Online	0.006 (0.003)*	0.019 (0.013)
Subsample estimates		
Non Remedial ($N = 193,522$)	−0.031 (0.003)***	−0.127 (0.010)***
Ever-Remedial ($N = 305,091$)	−0.036 (0.002)***	−0.140 (0.008)***

TABLE 4 *(Continued)*

Individual Fixed-Effects Estimates for Online Performance Gaps, by Student Subgroup

	Course Persistence	Standardized Course Grade
GPA in 1st Term Face-to-Face Courses		
Full-sample estimates		
Online Format (Low GPA)	−0.048 (0.003)***	−0.158(0.012)***
High GPA*Online	0.019 (0.004)***	0.046 (0.014)***
Subsample estimates		
High GPA ($N = 259,355$)	−0.030 (0.002)***	−0.126 (0.008)***
Low GPA ($N = 170,219$)	−0.048 (0.003)***	−0.162 (0.012)***

Note. N represents the total number of courses taken by this subgroup. All equations also include previous online enrollment, time fixed effects, and academic subject fixed effects, where the latter is applied to subject categories that have multiple subdisciplines (see Table 2). Models on course persistence also include a control for the average persistence rate in that course. Standard errors for all models are clustered at the student level.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level

In terms of age, while both older and younger students showed significant negative coefficients for online learning, the estimates for older students (age 25 or above at college entry) were significantly weaker than those for younger students, for both course persistence and standardized course grade. In face-to-face courses, older students were slightly *less* likely than younger students to persist (0.94 vs. 0.95); however, in online courses, older students were slightly *more* likely than younger students to persist (0.91 vs. 0.90).

Finally, to investigate the possibility that lower levels of academic preparation may moderate the effect of online learning, we initially used a variable indicating whether the student had ever enrolled in a remedial course (termed as *ever-remedial*). The p-value for the F test on the interaction term ($p = .098$) was significant for course persistence at the .10 level, indicating that students who entered college with lower academic preparedness had a marginally larger online performance gap in terms of persistence. However, using remedial enrollment as a proxy for academic skill level is somewhat problematic, because many students assigned to remediation education do not actually enroll in the courses (e.g., see Roksa, Jenkins, Jaggars, Zeidenberg, & Cho, 2009; Bailey et al., 2010). Thus the "nonremedial" population may in fact include some students who entered college academically underprepared but who skipped remediation. Moreover, a high proportion of students assigned

to remediation drop out of college in their first or second semester (Bailey et al., 2010; Jaggars & Hodara, 2011); thus, the student population narrows in subsequent semesters to only those who are the most motivated and well equipped to succeed in school. As a result, the estimates presented in Table 4 may underestimate the interaction effects between initial academic preparedness and course delivery format.

To investigate the role of academic preparation in another way, we conducted an additional analysis using students' GPA in their face-to-face courses in the initial term as a more precise measure of academic skill and motivation.[12] We used face-to-face GPA for two reasons: (1) GPA based on only one type of course format eliminated the impact of different course formats on GPA outcomes; and (2) face-to-face GPA represented academic performance in the bulk of courses taken in students' first semesters, as relatively few students took online courses in their first semester (7%) and very few took all their courses online in that term (3%). A "high" GPA is 3.0 or above, while "low" is below 3.0. As shown in Table 4, the interactive effect of academic preparation was magnified when using the GPA measure; p-values for the interaction terms were significant at the $p < .01$ level for both course persistence and standardized course grade, and the effect size of the interaction terms were much larger compared to those in the ever-remedial model.

The results from both the ever-remedial and GPA interaction models suggest that students with a stronger academic background had a narrower online performance gap, while students with weaker academic skills had a wider online performance gap. Thus differences between high-GPA and low-GPA students in face-to-face courses (0.96 vs. 0.94 for course persistence; 0.223 vs. −0.331 for standardized course grade) were magnified in online courses.

One potential concern with the student subgroup analyses is that heterogeneity in estimates could be due to subgroup differences in subject-area selection. For example, in terms of course persistence, females' relatively narrow online performance gap could be due to a female propensity to choose majors that happen to incorporate scaffolding for self-directed learning into their online courses. Accordingly, we tested the interactions between student characteristics and online course format within each academic subject area. Although not always significant across all subject areas, the size and direction of the coefficients generally echoed those presented in Table 4: Males, younger students, students with lower levels of academic preparation, and Black students were likely to perform particularly poorly in online courses relative to their performance in face-to-face courses.

Variation in Online Performance Gaps Across Course Subject Areas

In order to explore whether the online performance gap was wider or narrower in some academic subject areas than in others, we included a set of interaction terms between subject area and online course format into Equation 5, and examined the joint significance of all the interaction terms through an F test. The interaction test was strong and significant for both course persistence, $F = 3.60$, $p < .01$, and standardized course grade, $F = 4.66$, $p < .01$, indicating that the online performance gap did vary by academic subject area. To decompose the interaction effects, we separately estimated the coefficient for online learning within each subject area using Equation 5. Results are presented in Table 5, where each cell represents a separate regression using individual and time fixed effects; fixed effects are also included for academic subject areas that included multiple subdisciplines (as shown above in Table 2). Overall, every academic subject area showed negative coefficients for online learning in terms of both course persistence and standardized course grade, although the coefficients were insignificant for three subject areas (education, mass communication, and health & PE). Other subject areas' negative coefficients varied from relatively weak (e.g., natural science) to strong (e.g., English).

One potential explanation for the variation in online performance gaps across subject areas concerns the type of student who took online courses in each subject area. While the above model controlled for the *overall* effects of student characteristics on course performance, it did not control for how those characteristics may impact the *gap* between online and face-to-face performance. To do so, we added into the model interaction terms between course delivery format and the four key individual characteristics (i.e., gender, ethnicity, first-term face-to-face GPA, and age). The interaction terms between subject area and course format reduced in size but remained significant for both course persistence ($F = 3.36$, $p < .01$) and standardized course grade ($F = 3.86$, $p < .01$), indicating that the variation across subject areas in terms of online course effectiveness persisted after taking into account both the characteristics of students in each subject area, and how those characteristics might differentially influence performance in online versus face-to-face courses.

Another potential source of variation is peer effects based on the macro-level composition of students in each subject area. A given student may be exposed to higher performing peers in some subject areas and lower performing peers in others. If peer performance is differen-

TABLE 5

Individual Fixed-Effect Estimates for Online Performance Gaps, by Course Subject
(restricted to academic subjects with at least 5% online enrollment)

Subject	Course Persistence	Standardized Course Grade
Overall	−0.034 (0.002)***	−0.135 (0.006)***
Social Science	−0.056 (0.005)***	−0.207 (0.016)***
Education	−0.013 (0.012)	−0.066 (0.054)
Computer Science	−0.015 (0.008)**	−0.090 (0.031)***
Humanities	−0.044 (0.012)***	−0.161 (0.038)***
English	−0.065 (0.006)***	−0.279 (0.020)***
Mass Communication	−0.018 (0.037)	−0.004 (0.121)
Applied Knowledge	−0.027 (0.006)***	−0.157 (0.025)***
Applied Profession	−0.024 (0.004)***	−0.111 (0.016)***
Natural Science	−0.017 (0.007)**	−0.039 (0.021)***
Health & PE	−0.014 (0.009)	−0.005 (0.040)
Math	−0.069 (0.016)***	−0.181 (0.046)***
p-value for joint interaction	< .001	< .001

Note. Standard errors for all models are clustered at the student level. All equations also include a dummy for previous online enrollment, time fixed effects, and academic subject fixed effects, where the latter is applied to subject categories that have multiple subdisciplines (see Table 2). Models for course persistence also include a control for the average persistence rate in that course.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

tially important in online versus face-to-face courses, then this exposure could widen a student's online performance gap in some subject areas, and narrow the gap in others.

To explore the potential impact of peer effects on online performance gaps in a given subject area, we created an indicator, *online-at-risk,* defined as students who are academically less prepared (with a first-term face-to-face GPA below 3.0) and who also have at least one of the other demographic characteristics indicating greater risk of poor online performance (i.e., being male, younger, or Black). We then calculated the proportion of online-at-risk students for each course and interacted this variable with the course delivery format. The interaction terms were negative and significant at the $p < .01$ level for both course outcomes, indicating that a student's own online performance gap was stronger when the student's classmates were at greater risk for poor online performance.

After controlling for student characteristics in all feasible ways, including peer effects, the interaction terms between academic subject areas and course delivery format were still significant at the $p < .01$ level for both course persistence ($F = 3.35$) and standardized course grade ($F = 3.88$), suggesting that subject areas varied in their online performance gaps for reasons that were not situated in the characteristics of their students. To provide a clearer understanding of this pattern, we restricted our analysis of each academic subject to course enrollments ($N = 39, 614$) among the group of students who tend to have the most minimal online performance gaps—i.e., students who were female, older, non-Black, and had a first-term face-to-face GPA above or equal to 3.0. Within this subsample of students, the online coefficients were nonsignificant for both course persistence and course grade in most of the subject areas, but they remained significantly and substantially negative in the subject areas of social science ($N = 3,126$; $\text{Coefficient}_{persistence} = -0.044$, $p < .01$; $\text{Coefficient}_{grade} = -0.110$, $p = 0.01$) and applied professions ($N = 12,924$; $\text{Coefficient}_{persistence} = -0.016$, $p = 0.03$; $\text{Coefficient}_{grade} = -0.056$, $p = 0.05$).

Discussion and Conclusion

In order to understand whether the online performance gap is wider or narrower among particular student subgroups and subject areas, the current study analyzed student course performance across a large swath of online and face-to-face courses using a statewide community college dataset. Overall, the online format had a significantly negative relationship with both course persistence and standardized course grade, indicating that the typical student had more difficulty succeeding in online courses than in face-to-face courses.

Importantly, however, the *size* of the online performance gap varied significantly across subgroups. Specifically, males, Black students, and students with lower levels of academic preparation had significantly stronger online performance gaps compared with their counterparts. These patterns also suggest that performance gaps between key demographic groups already observed in face-to-face classrooms (e.g., between male and female students, and between White and ethnic minority students) are exacerbated in online courses. This is troubling from an equity perspective: If this pattern holds true across other states and educational sectors, it would imply that the continued expansion of online learning could strengthen, rather than ameliorate, educational inequity.

We also found that the online performance gap is narrower for older students than younger students, giving them a slight edge over their

peers in online courses. This finding is intriguing, given that older community college students tend to have poorer academic outcomes overall (Calcagno, Crosta, Bailey, & Jenkins, 2007) due to family and employment obligations (Choy & Premo, 1995; Horn & Carroll, 1996). While older students performed more poorly in online courses than in face-to-face courses, for this population a slight decrement in performance may represent a rational trade-off. Some students with family and childcare obligations report that without the flexibility of online learning, they would take fewer courses each semester (Jaggars, 2014). As such, it may be sensible for older students to trade the ability to take an additional course for slightly poorer performance in that course.

In addition to variation across types of students, we also found that the online performance gap varied across academic subject areas. Some of this variability seemed due to peer effects: regardless of their own characteristics, students experienced wider online performance gaps when they took subjects in which online-at-risk peers tended to cluster. Perhaps in online courses with a high proportion of online-at-risk students, interpersonal interactions and group projects are more challenging and less effective than they would be with the same group of students in a face-to-face course; or perhaps instructors devote more attention to students who are obviously struggling in the online environment, leaving the remaining students with less support in their own efforts to self-direct their learning. Future research examining the mechanisms of peer effects within online courses may wish to examine these possibilities.

After removing the effects of measurable individual and peer characteristics, two subject areas still demonstrated significant online performance gaps: the social sciences (e.g. anthropology, philosophy, and psychology) and the applied professions (business, law, and nursing). Perhaps these subject areas require a high degree of hands-on demonstration and practice, making it more difficult for instructors to create effective online materials, activities, or assignments. Or perhaps the learning process in these subject areas requires intensive student–instructor interactions and student–student discussions, which studies have suggested are more difficult to effectively implement in the online context (e.g., Bambara, Harbour, Davies, & Athey, 2009; Jaggars, 2014).

Overall, our findings indicate that the typical student performed less well in online than in face-to-face courses, but this performance gap was wider for some students and narrower for others. To improve student performance in online courses, colleges could take at least three distinct approaches: screening, early warning, and scaffolding.

First, in terms of screening, colleges could redefine online learning as a student privilege rather than a right. For example, they could bar students from enrolling in online courses until they demonstrate that they are prepared to succeed in that context (for example, by earning a 3.0 or better GPA, or by successfully completing a workshop on online learning skills). However, this strategy may disadvantage some students, particularly older students, who legitimately require the flexibility of online coursework; what is worse, it could cause drops in enrollments if students interested in online learning are enticed to schools that do not have such screening requirements. As a variant on the screening strategy, colleges might consider limiting or eliminating the supply of online sections for course subjects in which a considerable proportion of students are at risk for performing poorly online. As is shown in Table 2, many colleges have already followed this approach by offering very few online courses in developmental education, where a large proportion of students are academically underprepared.

A second possibility is incorporating early warning systems into online courses in order to identify and intervene with individual students who are struggling. Early warning systems are becoming increasingly popular but may require a substantial outlay of up-front costs, as well as faculty or counselor time.

A third strategy is scaffolding: incorporating the teaching of self-directed learning skills into courses. This strategy would require the college to support both online and face-to-face instructors in developing materials, assignments, and other pedagogical processes that cultivate self-directed learning skills within the context of each instructor's specific discipline (e.g., see Ambrose, Bridges, DiPietro, Lovett, & Norman, 2010; Weimer, 2002). Such a systematic skill-building strategy would require substantial new investments in faculty professional development and support. Yet these investments could pay high dividends. The consistent relationship between self-directed learning skills and academic success (Farrington, Roderick, Allensworth, Nagaoka, Keyes, Johnson, & Beechum, 2012) suggests that building these skills may not only help close the online performance gap, but may also improve students' overall performance and long-term persistence in college.

Although many students currently perform more poorly in the online context, online coursework represents an indispensable strategy in postsecondary education, as it improves flexibility for both students and institutions and expands educational opportunities among students who are balancing school with work and family demands. Our results may help stakeholders involved in the planning, teaching, or supervision of

online courses to consider strategies that will improve student outcomes in these courses. However, our study addresses only the community college context, and in only one state. Additional research in other states, and particularly in the four-year college setting, is needed to gain further insight into the impact of individual characteristics and course subject areas on the online performance gap.

Notes

[1] Using a subsample of the same dataset, we (Xu & Jaggars, 2013) explored the overall impact of online learning using an instrumental variable (IV) approach, and found robust negative estimates on both course persistence and (among course completers) course grade. Although the IV approach allowed us to effectively isolate the causal impact of online course delivery, it also required us to restrict the analyses to a fairly homogeneous subsample. In this study, we use an alternative empirical approach which allows us to take advantage of the full student sample in order to examine differences between types of students and courses.

[2] This sample does not include students who were dual-enrolled during the fall term of 2004 ($N = 6,039$).

[3] There are four quarters in each academic year, which starts in summer and ends in spring. We also refer to a quarter as a *term* or a *semester*.

[4] SBCTC divides students into five quintiles of SES status, based on Census data regarding the average income in the census block in which the student lives.

[5] SBCTC provided the Classification of Instructional Programs (CIP 2000) codes for each course in the dataset, and we further classified courses into larger subject categories shown in Table 2 using the CIP codes by 2-digit series.

[6] SBCTC coded courses as face-to-face, online, or hybrid. In hybrid courses, online delivery can replace only 50% or less of course time. Given that less than 2% of courses were coded as hybrid, we combined hybrid and face-to-face courses in this analysis. In a robustness check, we excluded all hybrid courses, and the results were nearly identical to those presented in Tables 2 to 5.

[7] Given that one of the outcome variables (course persistence) is discrete in nature, we also used logistic regression as a robustness check for this analysis. The results are very similar to those presented in Table 3. We present the results from OLS estimates for easier interpretation.

[8] Means and standard deviations for a given course were based on all students in our dataset who took the course, whether online or face-to-face, at any time across the five-year period.

[9] Of course, not all students attempted both online and face-to-face courses. Across

all courses in the sample (N = 498,613), about 55% (N = 267,191) were taken by students who took a mixture of online and face-to-face courses; about 45% were taken by students who took an entirely face-to-face curriculum; and less than 1% were taken by students who took only online courses. Including students who have no variation in course delivery format does not bias the fixed effects estimator, as long as selection bias is constant within an individual. A smaller degree of within-individual variation would be problematic if it yielded an imprecise estimator; with large sample sizes, however, this is typically less of a concern. Indeed, as shown in Table 3, all the estimates have small standard errors and large *t*-statistics, indicating that the fixed effects model is delivering precise estimates. In a robustness check, we also limited the sample to students who took a mixture of online and face-to-face courses, and the resulting effect sizes and significance levels were almost identical to those reported here. For a detailed discussion of the properties of the fixed-effects estimator and key assumptions underlying fixed effects models using panel data, see Wooldridge (2002).

[10] For this robustness check, students who had no valid Social Security Number (e.g., international students) or those in special employment situations (e.g., self-employed) would be subject to a missing value for a given quarter; this limitation reduced the sample size to 297,767 for course persistence and 279,073 for standardized course grade.

[11] Note that, given the inclusion of a different interaction in each model shown in Table 4, the estimate for the "main effect" of online learning represents the effect for the demographic reference group (indicated in parentheses).

[12] The drawback to this indicator is that students without a valid first-term face-to-face GPA were dropped from the sample. These students may have withdrawn from all courses, earned only remedial credits (which do not award GPA points), or completed only online courses in their first semester. This exclusion resulted in a loss of 14% of the overall course sample. We were concerned that this reduced sample could differ from the original sample in terms of the overall impacts of online format on course outcomes. We checked this possibility by reconducting the overall online impacts analysis on this subsample, and results were nearly identical to those presented in Table 3.

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