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Adaptability to Online Learning: Differences Across Types of Students and Academic Subject Areas

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Abstract

Using a dataset containing nearly 500,000 courses taken by over 40,000 community and technical college students in Washington State, this study examines how well students adapt to the online environment in terms of their ability to persist and earn strong grades in online courses relative to their ability to do so in face-to-face courses. While all types of students in the study suffered decrements in performance in online courses, some struggled more than others to adapt: males, younger students, Black students, and students with lower grade point averages. In particular, students struggled in subject areas such as English and social science, which was due in part to negative peer effects in these online courses.

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1. Introduction

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,[1] 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 two-year colleges (Choy, 2002; Parsad & Lewis, 2008), where a large proportion of the population are nontraditional students (Kleinman & Entin, 2002).

However, given that most college students received their primary and secondary education in the face-to-face setting, online coursework may represent an adaptation challenge for many. In an attempt to understand how readily students adapt to online coursework—that is, the extent to which students perform as well online as they do face-to-face—a large body of research has compared outcomes between online and face-to-face courses. Results have been mixed across studies, with some finding positive results for online learning and others finding negative results (e.g., see Bernard et al., 2004; Zhao, Lei, Yan, Lai, & Tan, 2005; Sitzmann, Kraiger, Stewart, & Wisher, 2006; Jahng, Krug, & Zhang, 2007; U.S. Department of Education, 2010).

One potential cause for the wide variation in results across studies may lie in the different student populations and course contexts examined in each study. Some populations of students—for example, those with more extensive exposure to technology or those who have been taught skills in terms of time-management and self-directed learning—may adapt more readily to online learning than others (Gladieux & Swail, 1999; Jun, 2005; Liu, Gomez, Khan, & Yen, 2007; Muse, 2003; Stewart, Bachman, & Johnson, 2010). In addition, some academic subject areas may lend themselves to high-quality online learning experiences more readily than others (Jaggars, 2012) and thus may support students more effectively in their efforts to adapt. Below, we discuss in more

[1]The National Center for Education Statistics (2002) defines a nontraditional student as one who has any of the following seven risk factors: (1) part-time attendance, (2) full-time employment, (3) delayed postsecondary enrollment, (4) financial independence, (5) having dependents, (6) being a single parent, and (7) not possessing a high school diploma.

detail how these different contexts could impact the ease with which students adapt to online coursework. We begin with a review of research on the impact of student characteristics on online learning performance, focusing on students' gender, age, ethnicity, and prior academic performance.

In terms of gender, while several studies have found no differences between males and females in terms of their learning outcomes in online courses (e.g., Astleitner & Steinberg, 2005; Lu, Yu, & Liu, 2003; Ory, Bullock, & Burnaska,1997; Sierra & Wang, 2002; Yukselturk & Bulut, 2007), others have found that women perform significantly better than men (e.g., Chyung, 2001; Gunn, McSporran, Macleod, & French, 2003; Price, 2006; Rovai & Baker, 2005; Sullivan, 2001; Taplin & Jegede, 2001). To explain the stronger performance of women within their study of online courses, McSporran and Young (2001) examined course observation and student survey data. They concluded that the women in their sample were more motivated, more adept at communicating online, and more effective in scheduling their learning. In contrast, male participants accessed fewer course website pages and fewer discussion forum posts; they also had poorer time management skills and tended to be overconfident in terms of their ability to complete learning tasks and assignments.

The notion that women may perform more strongly than men within online courses should not be particularly surprising, given that women tend to have stronger educational outcomes across a variety of contexts and timeframes. For example, women are more likely to graduate from high school (Swanson, 2004, Heckman & LaFontaine, 2007), and among students who attend college, women are more likely to earn a degree (Diprete & Buchmann 2006; Goldin, Katz, & Kuziemko, 2006). A more compelling question for online researchers may be: Do women more easily *adapt* to online courses than men? Put another way, is the gap between male and female performance *wider* or *narrower* within the online context than within the face-to-face classroom context? Thus far, however, the moderating role of gender in terms of students' adaptability to online learning has been left unexplored.

Similarly, Black and Hispanic students may perform more poorly than White students in online courses (Newell, 2007). If this is so, the pattern would certainly be due in part to the fact that Black and Hispanic students tend to perform more poorly in college overall, given that they are systematically disadvantaged in terms of the quality of their primary and secondary schooling (Feldman, 1993; Allen, 1997; DuBrock, 2000; Wiggam, 2004). No studies thus far have explored the moderating role of ethnicity in terms of student adaptability to online courses—that is, no studies we are aware of have examined whether the ethnic minority performance gap is exacerbated by online coursework. However, some researchers (e.g., Gladieux & Swail, 1999) have raised concerns that online learning could widen the postsecondary access gap between students of color and White students because of inequities in terms of at-home computer and Internet equipment. For example, in 2009, only 52 percent of African Americans and 47 percent of Hispanics had high-speed Internet access at home (Rainie, 2010). Such disadvantages in terms of at-home technological infrastructure could affect these students' ability to perform well in online courses.

In terms of student age, some studies have found no relationship between age and satisfaction or performance in online learning (e.g., Biner, Summers, Dean, Bink, Anderson, & Gelder, 1996; Osborn, 2001; Wang & Newlin, 2002; Willging & Johnson, 2004), while others have found that older students are more likely to complete online courses than their younger counterparts (Dille & Mezack, 1991; Willis, 1992; Didia & Hasnat, 1998; Wojciechowski & Palmer, 2005). For example, in one study of online learning (Dille & Mezack, 1991), the average age of successful students was 28, as opposed to 25 for non-successful students. Colorado and Eberle (2010) have argued that older students' success in online learning may be due to increases with age in levels of rehearsal, elaboration, critical thinking, and metacognitive self-regulation, each of which may contribute to success in online coursework.

The notion that older students may perform more successfully than younger students in online courses is intriguing, given that older college students tend to have poorer academic outcomes overall. Perhaps due to family and employment obligations (Choy & Premo, 1995; Horn & Carroll, 1996), older community college students are less likely than younger students to earn any credential or to transfer to a four-year university (Calcagno, Crosta, Bailey, & Jenkins, 2007). If older students indeed adapt well to the online environment, then online learning should be encouraged among this population, as it would provide them with expanded postsecondary access and an academic advantage that they may not otherwise have (Hyllegard, Deng, & Carla, 2008).

In contrast to the large volumes of studies examining gender, ethnicity, and age as predictors of online success, very few studies (e.g., Hoskins & Hooff, 2005; Figlio, Rush, & Yin, 2010) have examined the role of students' pre-existing academic ability. Yet students with weaker academic preparation may also have insufficient time management and self-directed learning skills, both of which are thought to be critical to success in online and distance education (e.g., Bambara, Harbour, & Davies, 2009; Ehrman, 1990; Eisenberg & Dowsett, 1990; Liu et al., 2007). Thus, while one would expect students with lower levels of academic preparation to fare more poorly in any course compared to their better prepared peers, one might expect that performance gap to be even wider in the online context. Indeed, a recent experimental study comparing learning outcomes between online and face-to-face sections of an economics course (Figlio et al., 2010) found no significant difference between the two course formats among students with higher prior GPAs; however, among those with lower prior GPAs, those in the online condition scored significantly lower on in-class exams than did those in the face-to-face sections. That is, low-GPA students had more difficulty adapting to the online context than did high-GPA students.

Overall, the research on the impact of student characteristics on online success indicates that patterns of performance in online courses mirror those seen in postsecondary education overall: Women and White students are likely to perform more strongly online than their counterparts. However, most studies have focused on student characteristics as a straightforward predictor (e.g., do women perform better than men within an online course?) rather than focusing on their potential influence on students' adaptability to online learning (e.g., do women adapt more easily to online learning than do men, leading to a wider gender gap in online courses than in face-to-face courses?) As a result, there is limited evidence in terms of how the continued expansion of online learning may differentially impact different types of students.

Regardless of students' own characteristics, their adaptability to online learning may also differ by academic subject, as online courses might be more engaging or effective in some subject areas than in others. For instance, 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. In support of the notion that the effectiveness of online learning may differ across subject areas, a recent qualitative study (Jaggars, 2012) examined course subjects that students preferred to take online rather than face-to-face. Students reported that they preferred to take "difficult" courses (with mathematics being a frequently cited example) in a face-to-face setting, while "easy" courses could be taken online. Students also explicitly identified some subject areas that they felt were "poorly suited to the online context" (p. 8), such as laboratory science courses and foreign-language courses. Outside of these qualitative data, however, the field has no information regarding which subject areas may be more or less effectively taught online.

In this paper, we examine whether student adaptability to online learning (that is, students' performance in online courses compared to their own performance in face-to-face courses) varies across student characteristics and academic subject areas. Information on the moderating role of student characteristics can help institutions market online courses more aggressively to subgroups that are likely to benefit more strongly from them, while devising support systems for subgroups that may experience more difficulties in an online learning environment. Information on course subjects that are more or are less well-suited to online learning may help institutions allocate resources for online course development more effectively.

To investigate these issues, we take 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. Using a subsample of the same dataset, we (Xu & Jaggars, 2012) previously explored the overall impact of online learning on student outcomes through an instrumental variable (IV) approach[2] and found robust negative estimates on both course persistence and (among course completers) course grade, indicating that many students had difficulty adapting to the online context.

[2]Specifically, we used the distance from a student's home to college as an instrument for the student's likelihood of enrolling in an online rather than face-to-face section of a given course. To satisfy the assumptions underlying the IV and course fixed effects approach, the authors limited the sample to Washington residents enrolled in an academic transfer track and to courses offering both online and face-to-face sections.

Although the empirical strategy enabled us to effectively isolate the causal impact of alternative delivery formats on student performance, the sample constraints imposed by the IV approach resulted in a student sample that was fairly homogeneous in academic capacity, motivation, and type of courses enrolled. As a result, it is possible that the estimates in that study were driven by particular student or subject subgroups, while other subgroups may have had a stronger capacity to adapt to online coursework. Thus, in this study, we include all the courses taken by the entire degree-seeking student population and employ an individual fixed effects approach to examine whether the gap between online and face-to-face outcomes is stronger or weaker within various subgroups. The results show that males, younger students, Black students, and students with lower levels of prior academic performance had more difficulty adapting to online courses.

The remainder of this paper is organized as follows: section 2 describes the database and introduces our empirical strategies; section 3 presents the results regarding both the overall impacts of online courses and the heterogeneous impacts by subgroups; and section 4 discusses findings from the current study and presents policy recommendations.

2. Empirical Framework and Data

2.1 Data and Summary Statistics

Primary analyses were performed on a dataset containing 51,017 degree-seeking students who initially enrolled[3] 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[4] of enrollment, or approximately five 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.

[3]This sample does not include students who were dual-enrolled during the fall term of 2004 (*N* = 6,039).
[4]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*.

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[5] in which the student lives (hereafter referred to as SES), academic background variables (e.g., whether the student was dually 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; GPA 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,[6] course delivery format,[7] and 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. Because the aim of this paper is to understand the relationship between course delivery and course persistence and grade, as well as variation in these patterns across different academic subject areas, we excluded courses without a valid decimal grade (e.g., courses that were audited, had missing grades, or had grades of Incomplete or Pass/Fail) and

[5]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.
[6]SBCTC provides 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.
[7]SBCTC divides courses into three categories: face-to-face, online, and hybrid. Given that less than 2 percent of courses are offered through the hybrid format and that these courses include a substantial amount of on-campus time (i.e., online technology can only be used to displace 50 percent or less of course delivery), we have combined hybrid with face-to-face courses in this analysis. In a robustness check, we excluded all hybrid courses from the analysis, and the results were nearly identical to those presented in Tables 2 to 5.

courses missing academic subject information. The final analysis sample included 498,613 courses taken by 41,227 students.

The 34 Washington community and technical colleges vary widely from one another in terms of institutional characteristics. The system comprises a mix of large and small schools, and the institutions are located in rural, suburban, and urban settings. Table 1 describes institutional characteristics of the 34 community and technical colleges in fall 2004 based on statistics reported to the 2004 Integrated Postsecondary Education Data System (IPEDS) database. Compared to the national sample, Washington community colleges serve substantially lower proportions of African American and Hispanic students and slightly higher proportions of White students. The SBCTC system also serves lower proportions of students who receive federal financial aid. Compared to national samples, community colleges in the Washington State system are also more likely to be located in urban areas. In summary, Washington community colleges seem to more closely represent an urban and White student population than do community colleges in the country as a whole.

Table 1
Characteristics of Washington State Community and Technical Colleges Versus a National Sample of Public Two-Year Colleges

Variables	Public Two-Year (National)	Public Two-Year (Washington)
Demographics		
Percent of White students	65.89 (23.69)	67.06 (12.96)
Percent of Black students	14.22 (17.02)	3.82 (3.11)
Percent of Hispanic students	8.54 (13.67)	5.68 (5.67)
Percent of Asian Students	3.94 (9.92)	5.33 (4.00)
Percent of students receiving federal financial aid	43.94 (18.71)	27.94 (10.63)
Percent of full-time students	64.53 (11.87)	64.93 (6.71)
Academics		
Graduation rates	29.03 (19.42)	32.79 (10.95)
First year persistence rates	57.73 (13.85)	57.85 (9.76)
Expenditure		
Instructional expenditures per FTE (in dollars)	5,261.52 (20,987.74)	4,848.71 (2,133.11)
Academic expenditures per FTE	1,003.05 (4,365.67)	578.26 (229.78)
Institutional expenditures per FTE	1,684.28 (4,236.92)	1,302.03 (1,391.40)
Student expenditures per FTE	1,037.52 (1,378.74)	1,237.12 (1,544.99)
Location		
Urban	39.40%	59.38%
Suburban	23.72%	21.88%
Rural	36.81%	18.75%
Observations (*N*)	1,165	34

Note. Standard deviations for continuous variables are in parentheses.

2.2 Empirical Models

As a baseline, we began with a basic ordinary least squares (OLS) model. This study focuses on two course outcomes: whether the student persisted through the course and the student's final decimal grade in the course. The key explanatory variable is whether students took each course through an online or a face-to-face format:

$$Y_i = \alpha_i + \beta\, online_i + \gamma\, X_i + \mu_i \qquad (1)^8$$

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

However, one of the major issues with exploring the effectiveness of alternative course delivery format is omitted student selection bias: Students who self-select into online courses may be substantially different from those in traditional courses; if any of these differences were not controlled for in the model, the estimate β would be biased. Indeed, in our previous analysis of the SBCTC data (Xu & Jaggars, 2012), we used an IV approach to construct a rigorous causal estimate of the effect of online versus face-to-face coursework; we compared the IV results to a *simpler* OLS-based approach and found that the straightforward OLS approach underestimated the negative impacts of online learning.

To deal with omitted student selection bias in the current analysis, we took advantage of the data structure, which included multiple course observations for each student, and employed an individual fixed effects approach. As a result, the unobserved factors affecting the dependent variable were decomposed into two parts: those that are constant (e.g., gender) and those that vary across courses (e.g., course subject). Letting *i* denote the individual student and *c* each course, the individual fixed model is written as:

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

[8]Given that one of the outcome variables (course persistence) is discrete in nature, we also used logistic regression as a robust check for this analysis. The results resemble what is presented in Table 3. We present the results from OLS estimates for easier interpretation.

where σ_i captures all unobserved, course-constant factors that affect the course performance, whereas υ_{ic} represents unobserved factors that change across courses and affect Y_{ic}.. Averaging this equation over courses for each individual *i* yields:

$$\bar{Y}_i = \bar{\alpha}_{ic} + \beta \, \overline{Online}_i + \gamma \, \bar{X}_i + \sigma_i + \bar{\upsilon}_i \tag{3}$$

where $\bar{Y}_{ic} = T^{-1} \sum Y_{ic}$, 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:

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

where $\ddot{Y}_{ic} = Y_{ic} - \bar{Y}_i$ is the course-demeaned data on course outcome Y, and so on. The important thing about equation (4) is that through the within-individual transformation, the 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. 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 student adaptability to online learning: if the coefficient is negative, the same student tends to perform more poorly in online courses than in face-to-face courses; if it is positive, then the same student tends to perform better in online courses.

However, while we have effectively ruled out course-invariant biases, biases that vary with courses could still remain in equation (4). One source of such bias is particular course-level attributes that influence both online enrollment and course outcomes. For example, online courses may be more likely to be offered in later years or in certain subjects; if so, then estimates from equation (4) would be subject to bias if academic subject or timing of course enrollment are also related to course outcomes. To address the potential problem of varying probability of online enrollment across different course subjects and time, we further added time and academic subject fixed effects into the individual fixed model.

Beyond differences in the propensity to take an online course within certain timeframes or subjects, which can be addressed with fixed effects, we were most concerned about three other potential sources of selection. First, within a certain subject, there may still be variations across courses in the extent of difficulty. For example, advanced courses may be much more academically demanding than introductory courses. Thus if introductory courses are more or less likely to be offered online in comparison to advanced courses, then our estimate may be biased. We addressed this problem through a supplementary robustness check in which we focused only on courses taken in each student's initial term, when first-time students are limited to introductory courses.

The same strategy also helped address a second concern: that students may sort between course modalities based on their previous performance and experiences. For example, among students who took an online course in their initial term ($N = 2{,}765$), failure to earn a C or above in these courses reduced their probability of ever attempting another online course in later terms by 18 percentage points, holding all other individual characteristics constant. As a result, online adaptability estimates based on courses taken in later semesters may be positively biased. Focusing on courses taken only during the first term may help deal with this type of selection; this is the time when students are least likely to sort between course modalities in reaction to their performance in online courses, because they know little about online courses within the college and their own potential performance in these courses.

A third potential source of course-variant bias is individual characteristics that change across time that can have an impact on both online enrollment and course outcomes. A key characteristic in this regard might be working hours, which for many students fluctuate across time and could also have a direct influence on both course-taking patterns and course outcomes. The dataset included quarterly employment information for 60 percent of the course sample. Accordingly, as an additional robustness check, we conducted an individual fixed effects analysis (plus academic subject and time fixed effects) that also included individual working hours in each quarter as a covariate; results from this analysis are presented in Table 3 (in section 3).

3. Empirical Results

3.1 Online Course Enrollments Across Different Subjects

Across the 498,613 course enrollments in the sample, approximately 10 percent 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 humanities, where more than 19 percent of the enrollments between 2004 and 2009 were online. Social science was the second largest category with 18 percent online enrollments, followed by education and computer science, with approximately 15 percent of course enrollments online. Three other subject areas with above-average online enrollments were applied professions (13 percent), English (12 percent), and mass communication (11 percent). In contrast, online enrollments were extremely low in engineering (with less than 1 percent of enrollments online) as well as in developmental education and English as a second language (4 percent).

Overall across the subject areas, the online enrollment data reveal three general patterns. First, online courses tended to be more popular in arts and humanities subject areas and less popular in natural science areas. (Although astronomy and geology had high proportions of online enrollments, these fields were small and thus constituted only a low proportion of science courses overall.) Second, with a few exceptions, the proportions of online enrollments were fairly consistent among the subjects within each subject-area category. For example, social science subjects (e.g., anthropology, philosophy, and psychology) fluctuated within a narrow range between 18 percent and 24 percent. Finally, online enrollments were much more prevalent within college-level courses than within “pre-college” courses (i.e., developmental and ESL education).

Table 2
Proportion of Online Enrollments by Subject

Subject Area	Proportion of Enrollments Online	Total Enrollments
Humanities	**19.40%**	**16,548**
History	19.33%	10,675
Cultural Studies	16.94%	1,299
Other	20.27%	4,574
Social Science	**18.29%**	**60,400**
Anthropology	17.81%	32,894
Philosophy	18.13%	7,463
Psychology	18.71%	18,557
Other	24.36%	1,486
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 footnote 6 for information on how the subject areas were classified.

3.2 Students' Online Adaptability Overall

In descriptive terms, students' average persistence rate across courses was 94.12 percent, with a noticeable gap between online courses (91.19 percent) and face-to-face courses (94.45 percent). 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), also with a gap between online courses (2.77) and face-to-face courses (2.98). Table 3 presents the online coefficients for both course persistence and 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 course grades, indicating that most students had difficulty adapting to the online context.

Table 3
Coefficients for Online (Versus Face-to-Face) Learning

	Full Course Sample				Initial Semester Only	
	OLS (1)	**Individual FE (2)**	**Adding Time & Subject FE (3)**	**Adding Working Hours (4)**	**OLS (5)**	**Individual FE (6)**
Course Persistence						
Coefficient	−0.031***	−0.044***	−0.043***	−0.046***	−0.033***	−0.057***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.005)	(0.009)
Individual FE	No	Yes	Yes	Yes	No	Yes
Subject FE	No	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	No	No
Observations	498,613	498,613	498,613	297,767	65,467	65,467
Course Grade						
Coefficient	−0.215***	−0.257***	−0.265***	−0.282***	−0.312***	−0.283***
	(0.006)	(0.008)	(0.008)	(0.010)	(0.024)	(0.034)
Individual FE	No	Yes	Yes	Yes	No	Yes
Subject FE	No	No	Yes	Yes	No	No
Time FE	No	No	Yes	Yes	No	No
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, and a dummy variable for full-time college enrollment in that term.
***Significant at the 1 percent level.

Moreover, estimates based on the individual fixed effects model (specification 2), which accounts for unobserved individual characteristics, were 20 percent to 40 percent larger than those based on the OLS model; adding time and academic subject fixed effects (specification 3) and working hours (specification 4)[9] into the model yield similar or even larger estimates. These patterns strengthen the notion that students who were more disposed to take online course also tended to have stronger overall academic performance than their peers. As a result, straightforward OLS estimates may tend to *underestimate* the negative impacts of online course enrollment in the absence of key individual variables (that is, to *overestimate* students' abilities to positively adapt to online learning).

On the right side of Table 3, the sample is limited to only courses taken in a student's initial term to address student selection into course format based on their previous experiences with online learning at college. This is also the time when students were most likely to be constrained to introductory courses, which would help address possible correlations between course difficulty and probability of online offering. The size and significance of the negative estimates[10] of online learning remain for both course outcomes with the first-term-only analysis. These results strengthen the full sample analysis by indicating that the negative estimates persist after additional controls for student-level and course-level selection bias.

3.3 Adaptability Across Different Types of Students

In order to explore whether the gap between online and face-to-face outcomes 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. As a first step in each heterogeneity analysis, we included an overall interaction term between the given individual attribute and course format into

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[9]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 course grade.

[10]These results do not include a model with time or academic subject fixed effects because there is no variation by term and little variation by subject when individual fixed effects are applied; working hours also cannot be included, as working hours do not vary across courses in a given term, and are therefore automatically dropped from the individual fixed model when it is focused on only one term.

Equation 2; the corresponding *p*-value for each interaction term is reported in the last row of each panel. To better understand the meaning of each interaction, we then conducted separate analyses on each subgroup using the same model specification; and when necessary to interpret the main effects of student characteristics, we conducted supplemental analyses using Equation 1.[11]

Table 4
Individual Fixed-Effects Estimates for Online Learning, by Student Subgroup

	Course Persistence	Course Grade
Gender		
Female (*N* = 272,838)	−0.037 (0.002)***	−0.249 (0.009)***
Male (*N* = 225,775)	−0.054 (0.003)***	−0.288 (0.013)***
p-value for the interaction term	< .001	.051
Race		
White (*N* = 349,765)	−0.043 (0.002)***	−0.275 (0.009)***
Black (*N* = 19,067)	−0.054 (0.012)***	−0.394 (0.050)***
Hispanic (*N* = 13,687)	−0.050 (0.012)***	−0.283 (0.051)***
Asian (*N* = 42,841)	−0.034 (0.006)***	−0.189 (0.025)***
Other (*N* = 73,253)	−0.046 (0.005)***	−0.224(0.019)***
p-value for the interaction terms	.484	< .001
Age (in Fall 2004)		
Above 25 (*N* = 122,165)	−0.028 (0.003)***	−0.170 (0.014)***
Below 25 (*N* = 376,448)	−0.049 (0.002)***	−0.300 (0.009)***
p-value for the interaction term	< .001	< .001
Remediation Status		
No remedial courses (*N* = 193,522)	−0.040 (0.003)***	−0.252 (0.012)***
Took any remedial courses (*N* = 305,091)	−0.045 (0.002)***	−0.272 (0.010)***
p-value for the interaction term	.078	.017
GPA in 1st Term Face-to-Face Courses		
Equal to or above 3.0 (*N* = 259,355)	−0.039 (0.002)***	−0.250 (0.010)***
Below 3.0 (*N* = 170,219)	−0.058 (0.003)***	−0.314 (0.015)***
p-value for the interaction term	< .001	< .001

Note. *N* represents the total number of courses taken by this subgroup. Each cell represents a separate regression using individual fixed effects approach. All equations also include time fixed effects and academic subject fixed effects, where the latter is applied to subjects that have multiple disciplines as presented in Table 2. Standard errors for all the models are clustered at the student level.
***Significant at the 1 percent level.

[11]Given that Equation 2 includes individual fixed effects, the main effects of student characteristics (for example, of being female) on face-to-face course performance are automatically controlled for and therefore dropped from the model. However, our research question focuses on course-varying effects (i.e., the gap between online and face-to-face performance), and as such, there are sufficient degrees of freedom to include interactions between the online format and student characteristics in the model. Such interactions can still be interpreted similarly to an interaction in a model that includes its component main effects. However, in order to discuss the main effects of student characteristics, as is sometimes helpful to understand the larger pattern of results, we must use Equation 1.

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 course grade, though the interaction term was only marginally significant ($p = .051$) for course grade. These interactions have two valid interpretations: (1) men had more difficulty adapting to online learning than did women; and (2) while females outperformed their male counterparts on average across all courses, the gender performance gap was stronger in the online context than in the face-to-face context.

For students of different ethnicities, although all types of students were more likely to drop out from an online course than a face-to-face course, the size of this difference did not significantly vary across ethnic groups. In contrast, when we turn to grades among those who persisted in the course, the ethnicities strongly differed in their coefficients for online learning. For example, Black students had nearly twice the negative coefficient of Asian students. That is, the gap between Black and Asian student performance was much wider in online courses than it was in face-to-face courses.

In terms of age, while both older and younger students showed significant negative coefficients for online learning, the estimates for older students were significantly weaker than those for younger students, for both course persistence and course grade. Interestingly, while the main effect of age was positive in terms of course grade, the main effect was negative in terms of course persistence, indicating that older students, on average, were more likely to drop out from courses compared with their younger counterparts. To further assist in interpreting the moderating role of age, we predicted the course persistence rate separately for older and younger students within each type of course delivery format, based on the individual fixed effects model. Among face-to-face courses, the model-adjusted probability of course persistence was 95 percent for younger students and 94 percent for older students; however, in online courses, the pattern was reversed, with predicted probabilities of 90 percent for younger students and 91 percent for older students. That is, older students performed more poorly in online courses than in face-to-face courses; however, the decrement in performance was not as strong as that among younger students. Thus it appears that older students' superior adaptability to online learning lends them a slight advantage in online courses in comparison with their younger counterparts.

Finally, to investigate the possibility that lower levels of academic skill may moderate the effect of online learning, we initially used a variable indicating whether the student had ever enrolled in a remedial course (termed an *ever-remedial* student). The p-value for the F test on the interaction term ($p = .078$) was significant for course persistence at the .1 level and significant for course grade at the .05 level ($p = .017$), indicating that students who entered college with lower academic preparedness had more difficulty adapting to online courses. However, it is worth noting that one problem with using remedial enrollment as a proxy for academic skill level is that many students assigned to remediation education may not actually take the courses (e.g., see Roksa et al., 2009; Bailey, Jeong, & Cho, 2010). Thus the "non-remedial" 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 capacity 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 percent) and very few

[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 13 percent 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 re-conducting the overall online impacts analysis on this subsample, and results were nearly identical to those presented in Table 3 (e.g., estimates based on model 3 are $\text{coefficient}_{\text{persistence}} = -0.046$, $p < .01$; $\text{coefficient}_{\text{grade}} = -0.275$, $p < .01$).

took all their courses online in that term (3 percent). As shown in Table 4, the interactive effect of academic capacity 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 course grade, and the gap of the coefficients between the two groups was even wider compared to those in the ever-remedial model.

The results from both the ever-remedial and GPA interaction models indicate that students with stronger academic capacity tended to be less negatively affected by online courses, while students with weaker academic skill were more strongly negatively affected. The interaction also indicates that the gap in course performance between high- and low-skill students tended to be stronger in online courses than in face-to-face 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, the observed interaction between gender and online adaptability could be due to a female propensity to choose majors that happen to have higher-quality online courses. Accordingly, we tested the interactions between student characteristics and online adaptability within each academic subject area. Although not always significant across all subjects, the size and direction of the coefficients generally echoed those presented in Table 4: Males, younger students, students with lower levels of academic skill, and Black students were likely to perform particularly poorly in online courses relative to their performance in face-to-face courses.

3.4 Differences in Online Adaptability Across Course Subject Areas

In order to explore whether students adapt to online learning more effectively in some academic subject areas than in others, we included a set of interaction terms between subject area and online course format into specification 3,[13] 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, $F = 6.01$, $p < .001$, and course grade, $F = 13.87$, $p < .001$, indicating that student adaptability to online learning 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 3. Results are

[13]All models also include time fixed effects and academic subject fixed effects, where the latter is applied to those subjects that have multiple sub-disciplines, shown in Table 2.

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 sub-disciplines (as shown above in Table 2).

Table 5
Individual Fixed-Effect Estimate for Online Learning, by Course Subject
(restricted to academic subjects with at least 5 percent online enrollment)

Subject	Course Persistence	Course Grade
Overall	−0.043 (0.002)***	−0.267 (0.008)***
Social Science	−0.064 (0.005)***	−0.308 (0.018)***
Education	−0.016 (0.013)	−0.337 (0.059)***
Computer Science	−0.024 (0.008)***	−0.221 (0.041)***
Humanities	−0.052 (0.012)***	−0.190 (0.046)***
English	−0.079 (0.006)***	−0.394 (0.023)***
Mass Communication	−0.039 (0.038)	−0.277 (0.159)*
Applied Knowledge	−0.036 (0.007)***	−0.322(0.030)***
Applied Profession	−0.027 (0.004)***	−0.211 (0.018)***
Natural Science	−0.030 (0.007)***	−0.159 (0.025)***
Health & PE	−0.009 (0.010)	−0.300 (0.046)***
Math	−0.065 (0.016)***	−0.234 (0.056)***
p-value for the interaction terms	< .001	< .001

Note. Standard errors for all the models are clustered at the student level. All models also include time fixed effects and academic subject fixed effects, where the latter is applied to subjects that have multiple disciplines as presented in Table 2.
***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Overall, every academic subject area showed negative coefficients for online learning in terms of both course persistence and course grade. However, some had relatively weak coefficients, and three subject areas had insignificant coefficients for the outcome of persistence. The subject areas in which the negative coefficients for online learning were weaker than average in terms of both course persistence and course grades (indicating that students were relatively better able to adapt to online learning in these subjects) were computer science, the applied professions, and natural science.

One potential explanation for the variation in student adaptability across subject areas concerns the type of student who took online courses in each subject area. While we controlled for the overall effects of student characteristics in the above model, we did not control for how those characteristics may have impacted differences 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 = 2.55, p = .004) and course grade (F = 5.55, p < .001), indicating that the variation across subject areas in terms of online course effectiveness persisted after taking into account the characteristics of students in each subject area and how well those types of students adapted to online learning.

Another potential source of variation in online impacts across academic subjects is peer effects based on the macro-level composition of students in each subject area. While the models above control for how an individual's characteristics affect his or her own performance, they do not control for how the individual's performance is affected by the other students in his or her courses. Descriptive supplemental analyses indicate that peer effects could be a salient issue: Students with higher first-term GPAs in face-to-face courses (hereafter referred to as *first-term f2f GPA*) tended to cluster their course enrollments in subject areas with weaker negative coefficients for online learning. While the average first-term f2f GPA across our sample was 2.95, it was higher among course enrollees in the natural sciences (3.02), computer science (3.02), and the applied professions (3.03). In the natural science sub-discipline of physics, in which course enrollees had a particularly high first-term f2f GPA (3.12), the negative coefficients for online learning in terms of both course persistence (p = .306) and course grade (p = .802) were no longer significant. In contrast, subject areas with enrollees who had low first-term f2f GPAs (e.g., 2.89 in English and 2.82 in social science) had stronger negative estimates for online learning, as shown in Table 5. These descriptive comparisons suggest that a given student is exposed to higher performing peers in some subject areas and lower performing peers in others and that this could affect his or her own adaptability to online courses in each subject area.

To explore the potential impact of peer effects in terms of how well students adapt to online courses in a given subject area, we created an indicator, *online-at-risk*, defined as students who are academically less prepared (with a first-term f2f 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 persistence and course grade, indicating that an individual student's performance penalty in an online course was stronger when the student's classmates were having difficulty adapting to the online context.

To provide a clear illustration of the peer effect interaction, we estimated the online learning coefficient separately for courses where 75 percent or more students were online-at-risk and for courses where 25 percent or fewer were online-at-risk. In courses where 75 percent or more were online-at-risk ($N = 25{,}128$), the negative coefficients for online delivery were strong: −0.064 ($p < .01$) for course persistence and −0.359 ($p < .01$) for course grade. In contrast, in courses where 25 percent or fewer students were online-at-risk ($N = 201{,}539$), the negative impacts were nearly halved, to −0.035 ($p < .01$) for course persistence and −0.231 ($p < .01$) for course grade.

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 and course grade, indicating that there may have been intrinsic differences between subject areas in terms of the effectiveness of their online courses. 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 adapted best to the online delivery format—i.e., students who were female, older, non-Black, and had a GPA above or equal to 3.0 in their face-to-face courses in the initial term of college. Within this highly adaptable subsample with peer effects controlled, any remaining significant negative online coefficients in a given subject may indicate that the particular subject area is intrinsically difficult to adapt to the online context.

Within this subsample, the online coefficients were non-significant for both course outcomes in most of the subject areas, but they remained significantly and substantially negative in the subject areas of social science ($N = 3{,}136$; $\text{Coefficient}_{persistence} = -0.050$, $p < .01$; $\text{Coefficient}_{grade} = -0.195$, $p < .01$) and applied professions ($N = 12{,}924$; $\text{Coefficient}_{persistence} = -0.020$, $p = 0.01$; $\text{Coefficient}_{grade} = -0.135$, $p < .01$).

4. Discussion and Conclusion

In order to understand whether particular student subgroups may have more or less difficulty adapting to online coursework, the current study analyzed student 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 course grade, indicating that the typical student had difficulty adapting to online courses. While this negative sign remained consistent across all subgroups, the *size* of the negative coefficient varied significantly across subgroups.

Specifically, we found that males, Black students, and students with lower levels of academic preparation experienced significantly stronger negative coefficients for online learning compared with their counterparts, in terms of both course persistence and course grade. These results provide support for the notion that students are not homogeneous in their adaptability to the online delivery format and may therefore have substantially different outcomes for online learning (Muse, 2003; Wiggam, 2004; Hoskins & van Hooff, 2005; Jun, 2005; Stewart et al., 2010). These patterns also suggest that performance gaps between key demographic groups already observed in face-to-face classrooms (e.g., gaps between male and female students, and gaps 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 older students adapted more readily to online courses than did younger students. This finding is intriguing, given that older college students tend to have poorer academic outcomes overall. While older students still did more poorly in online than in face-to-face courses, for this population a slight decrement in performance may represent a rational trade-off: Given that a majority of older students assume working and family responsibilities, without the flexibility of online learning, they would have to take fewer courses each semester (Jaggars, 2012). As such, older students may be willing 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 relative effects of online learning varied across academic subject areas. While there may be intrinsic characteristics that render some subject areas better suited than others to online learning, our results also suggest that the macro-level composition of enrollments within a particular subject area impacts the effectiveness of its online courses, in two ways.

First, different types of students tend to cluster systematically into different academic subject areas. While some areas attract students with a strong ability to adapt to online coursework, others attract students who do not adapt well. Second, regardless of a particular student's own adaptability to the online environment, her performance in an online course may suffer if her classmates adapt poorly. English and social science were two academic subjects that seemed to attract a high proportion of less-adaptable students, thereby introducing negative peer effects. Perhaps in online courses with a high proportion of less-adaptable students, interpersonal interactions and group projects are more challenging and less effective, which then negatively impacts everyone's course performance; or perhaps instructors devote more attention to students who are struggling most to adapt, leaving the remaining students with less support in their own efforts to adapt. Future research examining the mechanisms of peer effects within online courses may wish to examine these possibilities.

Outside of the effects of self and peer adaptability to online courses in general, two academic subject areas appeared intrinsically more difficult for students in the online context: the social sciences (which include anthropology, philosophy, and psychology) and the applied professions (which include business, law, and nursing). Perhaps these subjects 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 subjects 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 et al., 2009; Jaggars, 2012).

Overall, our findings indicate that the typical student has some difficulty adapting to online courses, but that some students adapt relatively well while others adapt very poorly. To improve student performance in online courses, colleges could take at least four distinct approaches: screening, scaffolding, early warning, and wholesale improvement.

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 likely to adapt well to the online 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. The variation across student demographic groups also has a consequence for individual academic departments, as more-adaptable students tend to cluster in some academic areas while less-adaptable students cluster in others. As a variant on the screening strategy, colleges might also consider an online course allocation strategy. For example, colleges might consider limiting or eliminating the supply of online sections for course subjects in which a considerable proportion of students are at risk to adapt poorly. 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 strategy is scaffolding: incorporating the teaching of online learning skills into online courses in which less-adaptable students tend to cluster, such as English composition. This strategy would require the college to work with instructors to develop materials and assignments that develop online learning skills and deploy them in the selected courses. A potential drawback to this strategy, however, is that some students might enroll in several "scaffolded" courses and become bored and frustrated with the now-unnecessary online learning skill exercises.

A third possibility is incorporating early warning systems into online courses in order to identify and intervene with students who are having difficulty adapting. For example, if a student fails to sign in to the online system, or fails to turn in an early ungraded assignment, the system could generate a warning for the instructor or for the college's counseling department, who could in turn call the student to see if he or she is experiencing problems and discuss potential supports or solutions. Early warning systems are becoming increasingly popular but may require a substantial outlay of up-front costs, as well as faculty or counselor time.

The first three strategies assume that the majority of online courses remain static in their quality, while the students enrolled in them improve their online skills. The fourth strategy, improvement, would instead focus on improving the quality of all online courses taught at the college, to ensure that their learning outcomes are equal to those of face-to-face courses, regardless of the composition of the students enrolled. Such an improvement strategy would require substantial new investments in course design, faculty professional development, learner and instructor support, and systematic course evaluations.

Although many students face challenges in adapting to online learning, online coursework represents an indispensible 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 students' ability to adapt to online courses.

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