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## Abstract

Using a unique dataset containing nearly 600,000 courses taken by 51,017students who entered one of Washington State's 34 community colleges in 2004, this study tracks students across five years, examining their online course enrollment patterns, overall online course performance, and possible heterogeneity of online course outcomes by academic subject as well as by student characteristics. We use an individual fixed effects strategy that controls for unobservable individual characteristics that may influence student selection of online vs. face-to-face courses. Our analyses show robust negative estimates for online learning on both course retention and course grade. In addition, we also find that the estimated impact of taking a course online rather than face-to-face varies by course subject, as well as by student characteristics, with stronger negative coefficients among males, younger students, black students, and students with lower academic capacity.


## 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 job 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 non-traditional students. (Kleinman & Entin, 2002).

Despite the rapid growth and high hopes surrounding distance education in postsecondary institutions, however, questions remain regarding its effectiveness. A large body of research has explored associations between course mode and student learning outcomes. However, results have been mixed across studies, with some finding positive results for online learning and others finding negative results (e.g., see Zhao, Lei, Yan, Lei, & Tan, 2005; Sitzmann, Kraiger, Stewart, & Wisher, 2006; Jahng, Krug, & Zhang, 2007; Figlio et al. 2010; Xu & Jaggars, 2011). One potential cause for the wide variation in results across studies may lie in the different contexts examined in each study, including the academic subject of the sample courses, and the overall characteristics of the sampled students.

First, students may substantially vary in the extent to which they can easily adapt to the online learning environment, and as a result, student characteristics can serve as

[1] The National Center for Education Statistics (NCES) has listed seven risk factors including 1) part-time attendance, 2) full-time work, 3) delayed postsecondary enrollment, 4) financial independence, 5) having dependents, 6) being a single parent, and 7) not possessing a high school diploma. A non-traditional student is one who has any of these characteristics (National Center of Education Statistics, 2002).

important moderators with online success (Muse, 2003; Wiggam, 2004; Hoskins & Hooff, 2005; Jun, 2005; Stewart, Bachman, & Johnson, 2010). One of the learner characteristics that have often been the focus of research in distance education is gender, though the effects of this variable are inconclusive with regard to student experiences and success. While some studies show that gender was unrelated to learning outcomes in online courses (e.g. Astleitner & Steinberg, 2005; Lu et al., 2003; Ory, Bullock, & Burnaska,1997; Sierra & Wang, 2002; Yukselturk & Bulut, 2007), others suggest that male and female students experience the online environment differently in several ways, such as motivations, perceptions, study habits, communication behaviors, which lead to gender gap in online course performance in favor of females (e.g. Chyung, 2001; Gunn et al., 2003; Price, 2006; Rovai & Baker, 2005; Sullivan, 2001; Taplin & Jegede, 2001). For example, Mcsprran and Young (2001) analyzed course observation, student performance and student survey data from an introductory undergraduate course and found that the online format favors women, who seem to be more motivated, better at communicating online and at scheduling their learning. In contrast, male participants accessed fewer course website pages and fewer discussion forum posts; they were also worse in time management skills and tended to be over-confident about their ability to complete learning tasks and assignments ahead online. The authors thus suggested that males in distance education might need more discipline that classroom sessions usually provide.

Similar inconsistencies were also found for the moderating role of age in online performance. Some studies (e.g. Biner et al., 1996, Osborn, 2001; Wang & Newlin, 2002; Willging & Johnson, 2004) indicated that the age of the learners was unrelated to satisfaction or performance in online learning while several other studies (Dill & Mezack, 1991; Willis, 1992; Didia & Hasnat, 1998; Wojciechowski & Palmer, 2005) found that older students are more likely to complete online courses than their younger counterparts. Dill and Mezack (1991), for example, found that the average age of successful students in their study was 28 as opposed to an average age of 25 for non-successful students, where "success" was defined as earning a C or above in the course studied. One possible explanation for this aged difference is the correlation between age and self-regulated characteristics. According to Colorado and Eberle (2010), older students have higher levels of self-regulated learning characteristics, especially in the areas of rehearsal, elaboration, critical thinking, and metacognitive self-regulation, which all contribute to online success.

In contrast to the large volumes of studies student demographic characteristics as potential predictors of online success, very few studies (e.g. Hoskins & Hooff, 2005; Figlio, Rush, & Yin, 2010) have examined the moderating role of student academic ability in online performance. Yet, student ability may substantially influence online learning experiences: students with weaker academic preparation might suffer more from technical difficulties, or might 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, 2009; Ehrman, 1990; Eisenberg & Dowsett, 1990) 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 groups overall but noted that among students with low prior GPAs, those in the online condition scored significantly lower on in-class exams than did those in the face-to-face sections. A common thread among all the studies examining the moderating role of individual characteristics is a strong recommendation that further research be conducted in this burgeoning field, as most of the studies involve small samples of students in a single course.

In addition to student characteristics, the relative effectiveness of online course delivery may also differ by academic subject. 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. And to the extent that the online environment requires stronger student time-management and self-directed learning skills, subjects that require disciplined pacing, with each new concept or skill requiring mastery of a previously-presented concept, might be more difficult for students in the online environment. In contrast, both instructors and students may find online learning easier in subjects where less hands-on interaction is required in the learning process, or where topics are not tightly building upon previous material. Indeed, a recent study (Jaggars & Edgecombe, 2012) that explores online course choices in community colleges found that students generally preferred to take more difficult courses, such as math, face-to-face to take advantage of teachers' step-by-step instructions and synchronous verbal communication. Students have also explicitly identified some subject areas that are too "poorly-suited to the online context" (p. 8), such as lab science courses and foreign-language courses that usually require hands-on instruction and practice. These findings have highlighted the possibility that online courses might be more suitable in certain subjects than others; yet, due to lack of data, no studies have performed large-scale analyses of the potential heterogeneity in online impacts on student outcomes across different subjects. Without hard data and analysis, one can only speculate about the moderating roles of individual characteristics and subject areas in online success.

Taking advantage of a large administrative data set that includes nearly 600,000 courses taken by 51,017 degree-seeking students who initially enrolled in one of Washington State's 34 community or technical colleges during the fall term of 2004, this paper bridges this research gap by examining the overall effectiveness of online courses, as well as possible heterogeneity by academic subject and student characteristics. Given that students may self-select into online vs. face-to-face sections of the same course, we use an individual fixed effects strategy that eliminates the influence of unobservable individual characteristics from the online treatment estimate. Further, to account for differences in online course availability across time and subjects, we augment the individual fixed strategy by adding subject and time fixed effects into the regressions, potentially controlling for biases related to between-term and between-subject selection.

Our analyses show robust negative estimates for online learning on both course retention and course grade, with the individual fixed estimates being consistently stronger than the corresponding OLS estimates across all model specifications. We also find that the estimated impact of taking a course online rather than face-to-face varies by course subjects as well as by student characteristics, with stronger negative coefficients among males, younger students, black students and students with lower academic capacity.

Drawing inferences about the heterogeneous impacts of online education based on a large dataset across multiple institutions, this study has the potential for providing valuable information to instructors teaching online courses. Knowledge about characteristics of students who may be at risk for withdrawal from online courses or poor performance outcomes can help instructors to take early interventions or provide additional support to maximize opportunities for these students. Administrators involved in decisions with respect to online course offerings and course designs may also benefit from this study, as the financial costs associated with losing students to dropout can be significant both to the institution and to the students. Hence identifying course subjects where students may suffer from greater difficulties with online learning environment allows better allocation of delivery resources. Finally, the existing research pertaining to persistence and performance in online courses is heavily focused on traditional students in four-year college and university settings and typically involves academically well-prepared students. In contrast, there is a scant of studies investigating online success and moderating factors among nontraditional adult learners in open-access colleges. Thus this study contributes to a better understanding of online effectiveness under the community and technical college setting, where most of the students are nontraditional and are often less prepared academically.

## 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[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 approximately five years. The dataset, provided by the Washington State Board of Community and Technical

[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."

Colleges (SBCTC), includes information on student demographics, institutions attended, transcript data on courses taken and grades received, and information on each course, such as course number, course subject, and course delivery format[4]. The dataset also includes information from Washington State Unemployment Insurance (UI) wage records, including individual employment status and working hours in each term. Excluded from the dataset are courses that were dropped early in the semester (prior to the course census date). Thus, in our study, “course dropout” denotes that a student paid full tuition for a course but did not persist to the end of the course. Because the aim of this paper is to understand the impact of course delivery on course outcomes including course dropout and course grade as well as variations of online course enrollment and effects across different course subjects, we excluded courses without a valid decimal grade (e.g. courses that were audited, missing grade, incomplete grade, pass/fail grade) and courses missing subject information. The final analysis sample includes 498,613 courses taken by 41,227 students. The 34 Washington community colleges vary widely from one another in terms of institutional characteristics. The system comprises a mix of large and small schools, as well as institutions 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 but slightly higher proportions of White students. The SBCTC system also serves lower proportions of students who receive federal financial aid. Compared to

[4] In the time period under study, an online course was defined as one in which 51% or more of the instruction and student-teacher interaction was online.

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.

### *2.2 Empirical Models*

To assess the effects of online course delivery, we use regression techniques, beginning with a basic OLS model. The study focuses on two course outcomes: whether the student withdraws from the course, and course final decimal grade (ranging from 0.0 to 4.0). The key explanatory variable is whether students took each course through an online or a face-to-face format:

$$Y_i = \alpha_i + \beta \text{ online}_i + \gamma X_i + \mu_i \qquad (1)$$ [5]

Where online is the key explanatory variable and is equal to 1 if the course is taken online; $X_i$ includes demographic attributes (e.g., age, gender, race, SES), academic preparedness (e.g., remedial status, previous dual enrollment), and semester-level information (e.g., total credits taken in this term); and $\mu_i$ is the error term. However, this simple regression equation likely suffers from omitted variable problems. Although the data set includes rich information about student characteristics, we can not rule out the possibility that there might exist unobserved factors that impact both online enrollment

[5] Given that one of the outcome variables (course withdrawal) 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 presented the results from OLS estimates for easier interpretation.

and course outcomes. If that were the case, the estimate β would be biased. In addition, the standard error of β is also problematic due to student clustering within schools.

To deal with these concerns, we took advantage of the data structure where we had multiple course observations for each student and employed an individual fixed effects approach. As a result, the unobserved factors affecting the dependent variable are decomposed into two parts: those that are constant (e.g. time management skills) 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:

$$Y_{ic} = \alpha_{ic} + \beta\ \text{online}_{ic} + \gamma\ X_{ic} + \sigma_i + \upsilon_{ic} \qquad (2)$$

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

$$\bar{Y}_i = \bar{\alpha}_{ic} + \beta\ \overline{\text{Online}}_i + \gamma\ \bar{X}_i + \sigma_i + \bar{\upsilon}_i \qquad (3)$$

where $\bar{Y}_{ic} = T^{-1} \sum Y_{ic}$ , and so on. Because $\sigma_i$ is fixed across courses, it appears in both equation (2) and equation (3). Subtracting (3) from (2) for each course yields:

$$\ddot{Y}_{ic} = \ddot{\alpha}_{ic} + \beta\ \text{On}\ddot{\text{l}}\text{ine}_{ic} + \gamma\ \ddot{X}_{ic} + \ddot{\upsilon}_{ic} \qquad (4)$$

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 $\sigma_i$ has disappeared. In other words, any potential unobserved bias would be eliminated through the individual fixed effects model if such bias is constant across courses.

However, while we have effectively ruled out course-invariant biases, biases that vary with courses would 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 semesters 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 subject fixed effects into the individual fixed model.

Beyond differences in the propensity to have an online course across terms and subjects, which can be addressed with fixed effects, we are most concerned about three remaining sources of selection. First, there are variations among courses in the extent of difficulty even within a single subject: Advanced courses can be much more demanding than introductory courses. If different levels of courses also vary in online course offerings, the estimate would be biased. We address this problem by focusing on courses taken by students only in their initial term, given that this is the time when students are often limited to introductory courses as future prerequisites.

In addition, focusing on courses in the initial term also helps address the second concern that students may sort between course modalities based on their previous performance and experiences. Indeed, among students who ever took an online course in their initial term (N=2,765), failure to earn a C or above in these courses reduces their probability of ever attempting another online course in later terms by 18 percentage points, holding all other individual characteristics constant. As a result, estimates of alternative delivery formats based on courses in later semester might be biased in favor of online courses. Hence, focusing on courses a student takes during their first term can 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 the least about the online course quality in their home college and their potential adaptability to an online learning environment.

Finally, another potential source of course-variant biases would be individual characteristics that change from one course to another, and have an impact on both online enrollment and course outcomes. One such characteristic might be employment status, which can fluctuate over time, and could also have a direct influence on both course taking patterns and course outcomes. The dataset included quarterly employment information for 60% of the course sample. Accordingly, as a robustness check, we conducted an individual fixed effects analysis (plus 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.

## 3. Empirical Results

### *3.1 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 Humanities, where more than 19% of the enrollments between 2004 and 2009 were online. Social Science was the second largest category with 18% online enrollments, followed by Education and Computer Science, with approximately 15% of course enrollments online. Three other subject areas with above-average online enrollments were Applied Profession (12.89%), English (12%), and Mass Communication (11%). In contrast, online enrollments were extremely low in Engineering, where less than 1% of the total enrollments were online. Developmental Education and English as Second Language (ESL) courses also were unusually unlikely to be online, with less than 4% of enrollments online.

To sum up, the examination of the proportion of online enrollments by subject reveals three general patterns: First, online courses are more popular in Arts and Humanities subjects; across all seven subject areas with above-average online enrollments, only one (i.e. Computer Science) was technology or science related. Although two science-area subjects (i.e. astronomy and geology) had a high proportion 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 are fairly consistent among the subjects under each subject-area category. For example, the subjects under the category of Social Science (i.e. anthropology, philosophy, psychology, and other) fluctuate within a narrow range between 18% and 24%. Finally, online enrollments seem more prevalent within college-level courses than within developmental and ESL education, where less than four percent of courses were taken online.

### *3.2 General Impacts*

The average withdrawal rate across courses is 5.88%, with a noticeable gap between online courses (8.81%) and face-to-face courses (5.55%). For courses where students persisted through to the end of the term (N=469,287), the average grade was 2.95 (on a 4-point scale), also with a gap between online courses (2.77) and face-to-face courses (2.98). Table 3 presents OLS estimates of the relative impact of online course format on both course withdrawal and course grade. The left side of the table includes courses taken during any term. The baseline regression (specification 1) includes a rich set of individual characteristics[6] but does not include any fixed effects. The results suggest that online course format has a significantly negative impact on both course retention and course grade. Specifically, students taking courses through the online format are on average more likely to withdraw from the course by approximately 3 percentage points; for students who persisted through the course, the average grade for online courses are lower compared to face-to-face courses by approximately 0.20 grade points, controlling for all available student characteristics. However, once accounting for unobserved individual characteristics through individual fixed effects model (specification 2), the estimated effects become noticeably larger for both outcome

[6] Covariates include a gender dummy variable, race dummy variables, socioeconomic status dummy variables, a dummy variable for receiving federal financial aid, a 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' prior or current enrollment in remedial courses, and a dummy variable for full-time college enrollment in the current term.

measures: the estimate for course withdrawal is magnified to 4.3 percentage points, a nearly 40% increase, and the estimate for course grade also increases by 20% to -0.26. Such a considerable increase in the estimated negative impacts not only lends support to the concern that unobserved pre-treatment characteristics may jointly influence both course format selection and course outcomes, but more importantly, it also provides insight into the direction of such bias --- students who are more likely to take a course through the online format are also those who are more likely to receive better course outcomes. As a result, straightforward OLS estimates may tend to *underestimate* the negative impacts of online course enrollment in the absence of key individual variables. To address remaining course-variant bias, we further added course subject and time fixed effects into the model (specification 3), which leads to approximately the same estimate for course withdrawal and a slightly stronger negative estimate for course grade compared to results based on specification 2. The last column (specification 4) presents estimates from a robustness check that added into the equation each individual's hours of employment in the current term. One tradeoff of this robustness check is that 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[7]; this limitation reduces the sample size to 297,767 for course withdrawal and 279,073 for course grade. The estimates based on specification 3 but adding working hours as an additional covariate are larger compared to the estimates from specification 3 for both course performance indicators. This observation implies that the direction of course-variant biases may share the same direction as individual fixed bias. If that were

[7] Students who had a valid SSN but were missing from the employment data for a given quarter were coded as "not working" during that quarter.

the case, the individual fixed estimates presented in column 2 and 3 would underestimate the negative impact of online format in the presence of course-variant biases.

On the right side of Table 3, we limit the sample to only courses taken in a student's initial term. These results do not include a model with time or subject fixed effects because there is no variation by term and little variation by subject when individual fixed model is applied; hours as a robust check has also been omitted dhere because working hours do not vary across courses in a given term and would therefore be automatically dropped from the individual fixed model. Interestingly, the negative impacts become consistently larger than when the entire course sample is used. Based on the individual fixed effects model (specification 6), students who initially attempted an online course are more likely to withdraw from these courses by 5.7 percentage points compared to face-to-face courses they are taking at the same time. This estimate is almost 33 percent larger than the corresponding estimate based on the full course sample. Similarly, the estimate on course grade is -0.28, approximately 11% larger compared to the estimate based on the full course sample.

One concern about the first-term-only estimates is that a high proportion of underprepared students drop out of college in their first or second semester (Bailey, Jeong, & Cho, 2010; Jaggars & Hodara, 2011); thus, the difference between the estimates based on the full course sample and those on the initial term might be due to the variations in student profiles in these analyses. To address this concern, we further narrow the first-term analysis on courses (N=14,798) taken by students who at least persisted into the second year of their college career (fall 2005). Yet, the estimates, 0.056 for course withdrawal ($p<0.01$) and -0.272 for course grade ($p<0.01$), are still considerably larger compared to the estimates based on the full course sample. These findings, together with the previous observation that students wisely select between course modalities based on their previous experiences and performance in online courses suggest that many students may rush into online courses without a thorough understanding of this course format (see section 4 for a detailed discussion). Finally, one problem with course grade is that we only observe this variable in courses where student persist to the end of the course, which introduces sample selection issue into the estimate: First, students who persist to the end may be better prepared students and may bias the estimate if the retention rates are substantially different between course modalities; yet, this problem can be effectively fixed by individual fixed effects as long as the unobserved individual characteristics do not vary by course; another concern which individual fixed effects are not able to address is that courses where students persisted to the end may be better designed. As a result, the higher withdrawal rates associated with online format may lead to an observation of course grades in better designed online courses. If this were the case, our study would underestimate the negative impacts of online course on student course grades.

### *3.3 Heterogeneity Among Different Course Subjects*

Our results have highlighted the potential penalty imposed through the online course delivery format on course outcomes. However, the analyses thus far have not taken into account possible heterogeneous effects of online courses across different subjects. We explored potential heterogeneity across subject by including a set of interaction terms between subject and course format, and examined the joint significance of all the interaction terms through an *F* test. The interaction test was strong and significant for both course withdrawal, $F = 6.01$, $p < .001$, and course grade, $F = 13.87$, $p < .001$, indicating that the estimated impact of online course-taking does vary by academic subject. To decompose the interaction effects, we separately estimated the impacts of the online format within each subject area. Results are presented in Table 4, where each cell represents a separate regression using individual and time fixed effects; subject fixed effects are also included for subjects that have multiple sub-disciplines as presented in Table 2 (e.g. humanities, applied knowledge, science etc.).

The subjects with comparatively smaller negative online impacts (i.e. below average) on both course withdrawal and course grades are Computer Science, Applied Profession, and Science. It seems likely that students in these subject areas have stronger academic skills, particularly in programs such as nursing, which in most community colleges is a selective major. And indeed, the percentage of remedial students (i.e. students who ever enrolled in remedial courses) was generally lower in these subject areas: On average, 61% of courses in our sample were taken by students who ever enrolled in remedial courses; this this percentage is slightly smaller in the subject area of Science (58%), and much smaller in Computer Science (50%) and the applied professions (47%). In “nursing and medical assistance,” where a particularly low proportion of courses were taken by remedial students (39%), the negative impact of online learning on course withdrawal was insignificant and small (coefficient <0.001, $p=0.988$) while the impact on course grade was less than one fourth of the negative impact overall (coefficient = -0.065, $p$=0.013) . In contrast, in subjects where a large proportion of courses were taken by remedial students (e.g., in English, where 68% of the courses were taken by students ever enrolled in remedial courses), the negative impacts of online format are much higher. This suggests that individual academic motivation and capacity may strongly interact with the impacts of online effectiveness on student learning.

### *3.4 Heterogeneity Among Different Types of Students*

In addition to course subjects, student characteristics may also interact with the impact of online course-taking. Therefore, we explored potential heterogeneity in the impact of online courses in terms of a set of key individual attributes including gender, age, remediation status, and race. The results are presented in Table 5. As a first step in each heterogeneity analysis, we included an overall interaction term between the given individual attribute and course format; the corresponding *p*-value for each interaction term is reported in the last row of each panel. We then conducted separate analyses on each subgroup using the same model specification.

Results indicate that the negative estimate for online course-taking does vary by type of student. In terms of gender, while females' estimated impact on course dropout is still significant, it is significantly weaker than that of their male counterparts. However, in terms of the course grade outcome, females and males have similar estimated impacts for online learning.

In terms of age, while both older and younger students had significant coefficients for online learning, the estimates for older students were significantly weaker than those of younger students, for both course withdrawal and course grade.

As for remediation status, the *p* value for the *F* test on the interaction terms was not significant for course withdrawal and only marginally significant for course grade, indicating that students who enter college with lower academic preparedness do not strongly differ from more-prepared students across the long-term in terms of their performance in online courses. However, it is worth noting that one problem with using remediation enrollment as a proxy for academic capacity is that many students who are 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 underprepared students drop out of college in their first or second semester (Bailey, Jeong, & Cho, 2010; Jaggars & Hodara, 2011) ; thus, this population is likely narrowed 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 5 may underestimate the interaction effects between initial academic preparedness and course delivery format. In view of this problem, we conducted a robust check on the potential interactional effects of academic capacity on online learning by using students' GPA in their face to face courses as a more precise proxy of academic motivation and capacity[8]. As shown in Table 5, the *p* values for the *F* test on the interaction terms were significant at 0.01 level for both course withdrawal and course

[8] We used students' GPA in their face-to-face courses instead of GPA overall to eliminate the impact of taking online courses on course outcomes. However, a drawback to use this indicator is that courses taken by students who took all of their courses online ($N_{course}$= 9,573) were therefore subject to missing face-to-face GPA values. As a result, the reduced course sample might be substantially different from the original sample in terms of the impacts of online format on course outcomes. Yet, we checked this possibility by re-conducting the overall online impacts analysis on the course sample with valid face-to-face GPA values and the results were almost the same as those presented in Table 3.

grade, indicating that academic capacity indeed influence the impacts of online effectiveness on student learning.

Finally, for students of different ethnicities, although each ethnic group is more likely to drop out from an online course than a face-to-face course, there is no significant between-group difference in terms of such impacts. In contrast, when we turn to course grades, the ethnicities strongly differ. For example, black students experience significantly larger penalty in terms of course grade in online courses, which is more than twice the negative impact on Asian students.

We were concerned that heterogeneity among different types of students might be due to systematic variations of course enrollments in different subjects among different subgroups. For example, the observed interaction between gender and online impacts may be because females are systematically more likely to enroll in course subjects where online courses are associated with lower penalty. Accordingly, we tested the student-heterogeneity interactions within each subject. Although not always significant across all subjects, the results generally echo those presented in Table 4 that males, younger students, students with lower initial academic ability and black students are particularly at risk in online courses.

## 4. Discussion and Conclusion

Researchers, practitioners, and policy makers are engaged in vigorous debate about the effectiveness and future promise of online learning in higher educational institutions. In an attempt to contribute reliable evidence on community college students' online course performance and possible variation of online impacts across subjects as well as by student characteristics, the current study uses a unique dataset to compare online and face-to-face course outcomes in a large state community college system. Our analysis shows that the online format has a significantly negative impact on both course retention and course grade, and that this relationship remains even after controlling for unobserved individual characteristics using individual fixed techniques.

Yet, our heterogeneity analyses reveal wide variations across subjects and across student type. Specifically, we find that subjects with higher proportion of college ready students have weaker and sometimes non-significant estimates in terms of the negative impact of taking a course online, suggesting that individual academic preparation may strongly interact with the effects of online learning. This possibility is supported by our heterogeneity analysis on student characteristics, where college-ready students experience smaller penalty in online courses compared to remedial students in terms of both course withdrawal and course grade. These findings can be reconciled with the general negative impact of online course by considering that although online delivery format may lower overall student persistence and performance, online sections may be effectively used in particular disciplines as an alternative to face-to-face sections with comparable quality. In contrast, colleges may consider limiting offerings of online courses in developmental education and entry-level courses where a large proportion of students are academically underprepared.

In addition to academic capacity, we have also identified a set of student demographic characteristics including gender, race, and age that have significant impacts on online learning effectiveness. These interactional effects provide support to the notion that students are not homogeneous in their adaptability to the online course delivery format, and may therefore have substantially different experiences and outcomes with online learning (Muse, 2003; Wiggam, 2004; Hoskins & Hooff, 2005; Jun, 2005; Stewart, Bachman, & Johnson, 2010). Hence, instructors may need to pay special attention to certain types of students in their online courses; instructors may need to identify effective intervention strategies to get these students motivated and involved in computer-mediated learning, such as to provide more strict time schedule as face-to-face classes usually do, organize frequent online discussions in which all students are encouraged to participate, make the course requirement and grading policy more clear and transparent, and offer more opportunities of interpersonal interactions between instructors and students . As for colleges, these findings nominate student academic preparation and demographic attributes as factors that should be taken into account when school administrators are considering increasing or reducing online course offering in a particular subject.

Finally, previous research suggests that students, particularly those without existing online learning experiences, tend to underestimate the workload in online course and be over-confident about their ability to complete online learning tasks, which may lead to early withdrawal or poor performance (e.g. Mcsprran & Young, 2001, Hare-Bork & Rucks-Ahidiana, 2012). This contention is supported by the finding in the current study that students experienced greater negative impact in online courses in their initial term than in later terms. Two sources might help explain this gap: First, students may actively adjust their perceptions about the difficulty, requirement, and interactional styles in an online learning environment based on learning experiences from their initial attempt and therefore get more prepared for online learning in later terms. In addition, students who find online courses too hard to adapt to may intentionally avoid online courses in later terms. Indeed, as indicated previously in the paper, unsuccessful online learning outcomes in initial terms reduces the likelihood of online enrollment by nearly 20 percentage points in later terms, indicating that students do choose wisely between alternative delivery formats based on their own experiences.

These findings suggest that students are not fully informed of what is expected from an online course and may therefore experience a shocking surprise in their initial attempt, many of which would lead to either early withdrawal or poor performance. This echoes previous findings that many students experience a shift in their expectations around various aspects of online courses, such as course difficulty, student responsibility, course communication, time management skills etc. after their initial attempt. During the period under study, the Washington system had already expended a substantial amount of resources to provide supports for online students, which includes student readiness assessment and online orientation.  However, most of these supports are provided on a passive basis, rather than being proactively pushed to students. Hence, it is desirable that colleges take active measures to get students fully informed of online course requirement prior to their enrollment. Examples of possible intervention strategies may include compulsory orientation session and readiness assessment, mentoring programs in which existing online students are invited to share their online learning experiences with new students, system-wide requirement for instructors to clarify means of communication, course requirement and assessment criteria at the beginning of the class.

Despite all the challenges that distance education is facing, online courses serve as an indispensible strategy to provide convenience and expand educational opportunities in community colleges. The findings of this study have practical implications for stakeholders involved in the planning, teaching, or supervision of online courses. By understanding the potential variations of online learning effectiveness across subjects and among different types of students, course modifications and early interventions may be implemented to benefit students. Future work is needed to gain further insight into the moderating roles of individual characteristics and course subject areas in online delivery impacts under the community college setting. Nonetheless, this paper makes an important first step in estimating the heterogeneous effect of alternative course format on student course learning outcomes.

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**Table 1 Characteristics of Washington State Community Colleges vs. National Sample of Public Two-Year Colleges**

| Variables | Public Two-Year (National) | Washington Community Colleges |
|---|---|---|

| | | |
|---|---|---|
| ***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 students receiving federal financial aid | 43.94 (18.71) | 27.94 (10.63) |
| Percent of fulltime students | 64.53 (11.87) | 64.93 (6.71) |
| ***Academics*** | | |
| Graduation rates | 29.03 (19.42) | 32.79 (10.95) |
| First year retention rates | 57.73 (13.85) | 57.85 (9.76) |
| ***Expenditure*** | | |
| Instructional expenditures per FTE (in dollars) | 5261.52 (20987.74) | 4848.71 (2133.11) |
| Academic expenditures per FTE | 1003.05 (4365.67) | 578.26 (229.78) |
| Institutional expenditures per FTE | 1684.28 (4236.92) | 1302.03 (1391.40) |
| Student expenditures per FTE | 1037.52 (1378.74) | 1237.12 (1544.99) |
| ***Location*** | | |
| Urban | 39.40% | 59.38% |
| Suburban | 23.72% | 21.88% |
| Rural | 36.81% | 18.75% |
| Observations (N) | 1165 | 34 |

Note: Standard deviations for continuous variables are in parentheses.

**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 Profession | 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 |
| 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 & PE | 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 and ESL | 3.85% | 48,592 |
| Engineering | 0.89% | 12,237 |
| | | |
| Total | 10.18% | 498,613 |

**Table 3 The Relative Effect of Taking a Course through the Online Format**

| | Full Course Sample | | | | Initial Semester Only | |
|---|---|---|---|---|---|---|
| | OLS | Individual FE | Adding Time & Subject FE | Adding Working Hours | OLS | Individual FE |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Course Withdrawal*** | | | | | | |
| Coefficient | 0.031*** | 0.043*** | 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 |

***Significant at the 1% level

Notes: 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.

**Table 4 Individual Fixed Estimate of the Relative Effects of the Online Format by Course Subjects (restricted to subjects with at least 5% online enrollments)**

| Subject | Course Withdrawal | Course Grade |
|---|---|---|
| Overall | 0.043 (0.002)*** | -0.263 (0.008)*** |
| | | |
| Social Science | 0.064 (0.005)*** | -0.303 (0.019)*** |
| Education | 0.017 (0.013) | -0.337 (0.059)*** |
| Computer Science | 0.024 (0.008)*** | -0.221 (0.041)*** |
| Humanities | 0.052 (0.012)*** | -0.187 (0.047)*** |
| English | 0.079 (0.006)*** | -0.393 (0.023)*** |
| Mass Communication | 0.039 (0.038) | -0.301 (0.159)* |
| Applied Knowledge | 0.036 (0.007)*** | -0.324(0.030)*** |
| Applied Profession | 0.027 (0.004)*** | -0.211 (0.018)*** |
| Science | 0.030 (0.007)*** | -0.159 (0.025)*** |
| Health & PE | 0.009 (0.010) | -0.287 (0.046)*** |
| Math | 0.065 (0.016)*** | -0.224 (0.057)*** |

***Significant at the 1% level **Significant at the 5% level * Significant at the 10% level
Notes: Standard errors for all the models are clustered at the student level. All models also include time fixed effects and subject fixed effects, where the latter is applied to subjects with multiple disciplines presented in Table 2.

**Table 5 Individual Fixed Estimate of the Effects of the Online Format by Student Characteristics**

| | Course Withdrawal | Course Grade |
|---|---|---|
| ***Gender*** | | |
| Male (N = 225,775) | 0.057 (0.003)*** | -0.295 (0.013)** |
| Female (N = 272,838) | 0.040 (0.002)*** | -0.266 (0.009)*** |
| P-value for the interaction term (s) | <0.001 | 0.0700 |
| ***Age (in Fall 2004)*** | | |
| Above 25 (N = 12,165) | 0.031 (0.003)*** | -0.194 (0.014)** |
| Below 25 (N = 376,448) | 0.052 (0.002)*** | -0.307 (0.009)*** |
| P-value for the interaction term (s) | <0.001 | <0.001 |
| ***Remediation Status*** | | |
| Took any remedial Courses (N = 305,091) | 0.049 (0.002)*** | -0.288 (0.010)*** |
| No remedial Courses (N = 193,522) | 0.042 (0.003)*** | -0.258 (0.012)** |
| P-value for the interaction term (s) | 0.117 | 0.054 |
| ***GPA in Face-to-Face Courses*** | | |
| Equal to or above 3.0 (N = 276,040) | 0.031 (0.002)*** | -0.238 (0.010)*** |
| Below 3.0 (N = 222,573) | 0.065 (0.003)*** | -0.314 (0.013)** |
| P-value for the interaction term (s) | <0.001 | <0.001 |
| ***Race*** | | |
| White (N = 349,765) | 0.046 (0.002)*** | -0.289 (0.009)*** |
| Black (N = 19,067) | 0.059 (0.012)** | -0.437 (0.050)** |
| Hispanic (N = 13,687) | 0.054 (0.012)** | -0.311 (0.051)** |
| Asian (N = 42,841) | 0.037 (0.006)*** | -0.187 (0.025)*** |
| Other (N = 73,253) | 0.049 (0.005)*** | -0.230 (0.019)** |
| P-value for the interaction term (s) | 0.643 | <0.001 |

***Significant at the 1% level

Notes: 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 subject fixed effects, where the latter is applied to subjects with multiple disciplines presented in Table 2. Standard errors for all the models are clustered at the student level.