Three Essays on the Impact of Cost-saving Strategies on Student Outcomes

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ABSTRACT

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For two decades, state financing of higher education has been on the decline and the situation has exacerbated since the onset of the economic recession, where the US state systems have resorted to a substantial cut of funding for higher education. Faced with the challenges of limited resources for financial pressure and an increasing demand, community colleges either have taken or are considering taking a series of cost-saving strategies. Some of the most prominent trends seen in the past decades include sharp expansions in distance education offerings through online coursework, an increasing reliance on part-time adjunct faculty, and a heated discussion about slashing expenditures on remedial education. Yet, many researchers argue that these strategies might be implemented at the cost of poorer educational quality and less desirable student outcomes. My dissertation assesses the impacts of several important strategies that community colleges are engaged in an era of financial constraints on student academic outcomes and educational equality.

In Chapter One, Shanna Smith Jaggars and I examine the fast growth of distance education and its impacts on student outcomes relative to traditional face-to-face delivery format. Based on a large administrative data set from Washington State, we found robust

negative estimates for online learning in terms of both course persistence and course grade. While all types of students in the study suffered decrements in performance in online courses, we also identified strong variations across subpopulations and academic subject areas. Chapter Two is prompted by the spiraling increase in part-time faculty hiring in open-access two-year community colleges. Based data from a large community college system, I identified a positive impact of taking one's first course in a subject area on his contemporaneous course performance but negative impacts on subsequent course outcomes and enrollment patterns. Finally, Chapter Three is inspired by the heated debate related to the effectiveness of college remediation. Exploiting discontinuities in students' probability of receiving remediation both around the college-level cut off and the cut off for short versus long sequence of remediation, I found small and insignificant impacts of remediation for students on the margin of needing remediation, but significantly negative influence on students receiving long sequence of remediation compared to those who received short sequence. These results suggest that some cost-saving strategies that colleges are recently engaged may bring negative impacts on student learning outcomes, and therefore policymakers and college administrators may need to take steps to ensure the quality of education offered to students before enacting policies that would incentivize an accelerated expansion of online enrollments, and overreliance on adjunct instructors. Additionally, the insignificant and negative impact of remediation suggests that the huge investment in remediation may not have been effectively utilized to serve its purpose and colleges will need to explore ways to improve its effectiveness.

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PREFACE

Higher education comprises the third largest portion of state general fund budgets, behind K–12 education and health care including Medicaid. But, unlike these functions, neither constitutional funding mandates nor linkages to federal matching dollars protect higher education. Indeed, for two decades, state financing of higher education has been on the decline (Kane & Orszag, 2003), and the situation has worsened since the onset of the economic recession, where the US state systems have resorted to a substantial cut of funding for higher education. A recent report that compares states' support of higher education in 2008, the last pre-recession budget year, and 2011 found that the average change in appropriations for all 50 states was negative 5.77 percent (Zumeta & Kinne, 2011).

Concomitant to the declining resources, however, is an escalating demand for higher education, particularly community colleges (U.S. Census Bureau, 2008; Pew Research Center, 2009), as college administrators have long observed in economic recessions (Betts & McFarland, 1995). Newly unemployed individuals may go into community colleges for working retraining, while those who are still in jobs may see further education as a vaccine against unemployment. Furthermore, loss of income may force individuals to enroll in lower-cost community colleges, when in better times they might have attended private or public universities.

Faced with the challenges of limited resources for increasing demand, community colleges have taken a series of measures to improve efficiency and reduce costs. Though not necessarily in response to cost pressures alone, some of the most prominent trends seen in the past decades include sharp expansions in distance education offerings through online coursework, an increasing reliance on part-time adjunct faculty, and a heated discussion about slashing expenditures on remedial education.

The extent to which some of the strategies can save on costs are potentially huge. Taking the employment of adjunct instructors as an example, adjunct faculty in 2003 on average earned $2, 836 per course compared to $10, 563 per course for full-time faculty in all community colleges (National Education Association, 2007); the cost difference is even wider considering that adjunct faculty typically receive minimal benefits from the college (NCES, 2001). As a result, replacing a full-time faculty member with an adjunct can potentially save up to 80% of the cost.

Similarly, college remediation is a widespread and expensive intervention, and the potential savings from slashing the expenditures on this costly investment on students can be enormous, particularly in community colleges. According to Clayton and Rodriguez (2013), remedial credits represent approximately 10 percent of all credits earned in community colleges, suggesting that the current cost of remediation may be nearly $4 billion dollars per year in the community college sector alone.

In contrast, the potential savings from distance education remain largely uncertain. Although it may seem self-evident that online courses are consistently cheaper than face-to-face courses, there is surprisingly little evidence on online and face-to-face course costs, and the conclusions drawn from relevant studies are mixed. Based on interviews with presidents, provosts, and other senior academic leaders at more than 25 higher education institutions,[1] Bacow, Bowen, Guthrie, Lack, and Long (2012) reported that most institutions indicated that online courses were at least as expensive as traditional courses, not only due to their substantial start-up costs (e.g., investments in technology, course design, and instructor training) but also due to recurring costs (e.g., those resulting from increased coordination demands and technical support). Despite the uncertainty about the actual cost of distance learning relative to traditional face-to-face classes, policy leaders in several states (e.g. Fain & Rivard, 2013; Chen, 2012; Texas Higher Education Coordinating Board, 2011) have strongly championed further expansions in online learning, assuming that online courses are necessarily more cost-effective.

Concomitant to the advocate and expansion of these cost-saving strategies is an escalating concern among many researchers that these strategies might be implemented at the cost of poorer educational quality and less desirable student outcomes (e.g. Leslie, 1998; Chamber, 2002; Bendickson, 2004). If this were the case, it would diminish the educational opportunities provided by community colleges, where large proportions of students are underprivileged. Yet, due to limited data availability, there is scant evidence regarding the potential impacts of these strategies on student outcomes.

My dissertation aims at assessing the impacts of several important strategies that community colleges are engaged in an era of financial constraints. In Chapter One, Shanna Smith Jaggars and I examine the fast growth of distance education and its impacts on student outcomes relative to traditional face-to-face delivery format in two sections. In the first section, we focused on the average effect using an instrumental variable approach to

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

control for student self-selection into online courses. Specifically, we used the distance from each student's home to his or her own college campus as an instrument for the likelihood of enrolling in an online course section of a given course. Analyses yield robust negative estimates for online learning in terms of both course persistence and course grade. In view of policy makers' deep interest in the potential heterogeneity of online learning across different subpopulations and different academic subject areas, in the second section, we extended the results from the IV analysis and explored potential variability of the effectiveness of online learning by different student subgroups and academic subject areas.[2] Based on an individual fixed approach, we found that 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.

Chapter Two reviews the spiraling increase in part-time faculty hiring and its potential influence on student course performance and subsequent course taking patterns. Based on a large administrative data set from a state community system, I explored how initial exposure to a particular subject area with an adjunct influenced both contemporaneous course outcomes and follow-on course taking behavior and performance. To address student self-sorting between instructors, I used semester-by-semester variation in the proportion of course sections taught by adjuncts in a particular

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[2] We initially hoped to conduct the heterogeneity analysis through the IV approach. Unfortunately, when we tested the validity of distance as an IV, it worked well with the transfer-oriented group (the final sample for this paper), but did not work well with the occupationally-oriented group. We felt that studying heterogeneity within that context (i.e., with occupational students excluded) would be too narrow a way to think about heterogeneity. Accordingly, we decided to focus on the average effect using a very rigorous design in section one, and used a less-rigorous but more-inclusive design to explore the heterogeneity question in-depth in a separate section.

college as an instrument for students' likelihood of taking the course with an adjunct; I further augment the instrumental variable approach by adding course fixed effects, therefore controlling for both between- and within- course selection bias. The results suggest that adjuncts have a positive impact on contemporaneous course performance but negative impacts on subsequent course outcomes and enrollment patterns. The negative effects on follow-on learning are particularly strong in fields that are more closely tied to an occupation.

Finally, Chapter Three is inspired by the heated debate related to college remediation and explores the impact of current remedial intervention on student outcomes. Based on a large administrative longitudinal data set that includes nearly 46, 000 students in 23 community colleges in Virginia, I examined the variations of the causal impacts of different levels of reading and writing remediation on short-term and long-term academic outcomes. The results suggest that the impacts of remediation are generally small in magnitude and statistically insignificant for students on the margin of needing remediation; yet, the estimates are negative and significant for lower-level remediation for most of the academic outcomes explored. In addition, subgroup analysis indicate that the negative impacts on students assigned to lower level remediation vary by institution, with stronger negative coefficients among colleges with higher proportion of students in remediation. This provides evidence to the hypothesis that assignment to remediation might worsen academic outcomes through "peer effects", where having more low-ability peers might induce greater negative effect on own outcomes. Finally, I found that the negative impacts also vary by types of students, with stronger negative impacts on females, younger students, and black students.

Results from the three essays suggest that some cost-saving strategies that colleges are recently engaged may bring negative impacts on student learning outcomes, and therefore policymakers and college administrators may need to take steps to ensure the quality of education offered to students before enacting policies that would incentivize an accelerated expansion of online enrollments, and overreliance on adjunct instructors. Additionally, the insignificant and negative impact of remediation suggests that the huge investment in remediation may not have been effectively utilized to serve its purpose and colleges will need to explore ways to improve its effectiveness.

Chapter One

Examining the Effectiveness of Online Learning within a Community College System

Section One: The Impact of Online Learning on Students' Course Outcomes: An Instrumental Variable Approach

1. Introduction

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

Although it may seem self-evident that online courses are consistently cheaper than face-to-face courses, there is surprisingly little evidence on online and face-to-face course costs. Most research on the topic is dated (e.g., Hawkes & Cambre, 2000; Jewett, 2000; Jung, 2003; Levine & Sun, 2002; Rogers, 2001; Virginia Community College

System, 2001; Whalen & Wright, 1999), and the conclusions drawn from relevant studies are mixed. Rumble (2003) discussed the complexities involved in making generalizations about costs across different types of courses and institutions and concluded that there can be no clear-cut answer as to whether online courses are indeed cheaper. Schiffman (2005) noted that development costs for online courses varied across institutions from $10,000 to $60,000 per course. Based on interviews with presidents, provosts, and other senior academic leaders at more than 25 higher education institutions,[3] Bacow, Bowen, Guthrie, Lack, and Long (2012) reported that most institutions provided distance education to better serve student needs rather than to save on costs. In fact, many interviewees believed that online courses were at least as expensive as traditional courses, not only due to their substantial start-up costs (e.g., investments in technology, course design, and instructor training) but also due to recurring costs (e.g., those resulting from increased coordination demands and technical support). Moreover, studies of online course costs have not taken into account the quality or effectiveness of the courses examined, and it is possible that online courses with high completion rates and strong learning outcomes require substantial investments to design and teach.

The second assumption underlying the cost-effectiveness argument—that online courses produce student outcomes comparable to those produced by face-to-face courses—is also based on relatively weak evidence. Although dozens of studies have compared student performance between online and face-to-face courses, most have been descriptive studies, with no controls for student self-selection. Moreover, the majority have focused on populations (e.g., K-12 students) or contexts (e.g., hour-long educational modules) that are not relevant to the typical online college course. Only a few random-

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

assignment or quasi-experimental studies have focused on semester-length college courses (Caldwell, 2006; Cavus & Ibrahim, 2007; Coates, Humphreys, Kane, & Vachris, 2004; Figlio, Rush, & Lin, 2010; LaRose, Gregg, & Eastin, 1998; Mentzer, Cryan, & Teclehaimanot, 2007; Odell, Abbitt, Amos, & Davis, 1999; Peterson & Bond, 2004; Schoenfeld-Tacher, McConnell, & Graham, 2001). Results of these studies are mixed, leading many college leaders to conclude that online learning at least "does no harm." However, two considerations limit the usefulness of this conclusion.

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

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

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

This paper builds on Xu and Jaggars' (2011) study of Virginia community colleges by focusing on a different region of the country and using an instrumental variable (IV) technique to control for unobserved confounding variables. Using a large administrative dataset from Washington State's community and technical college system, we used the distance from a student's home to college as an instrument for the likelihood of enrolling in an online rather than a face-to-face section of a given course. We augmented the IV strategy using course fixed effects, which allowed us to compare students who took the same course but were enrolled in sections with different delivery formats, potentially controlling for biases related to within- and between-course selection. To assess the effects of taking a course online rather than face-to-face, we explored two course outcomes: (1) course *persistence,* or whether a student remained in the course through the end of the semester; and (2) final course *grade* among those who persisted to the end of the course. Our analyses yielded robust estimates of negative impacts of online learning on both course persistence and course grade. Moreover, our IV estimates were consistently stronger than the corresponding OLS estimates across all model specifications, lending support to the Coates et al. (2004) argument that students tend to be positively selected into online coursework, which may bias the negative impacts of online learning toward zero when student self-selection is not well addressed.

2. Data

2.1 Data and Institutional Characteristics

The study used an administrative dataset of students who initially enrolled in one of Washington State's 34 two-year public community or technical colleges during the fall term of 2004. These first-time college students were tracked for approximately five years, through the summer of 2009. The dataset, provided by the Washington State Board of Community and Technical Colleges, included information on student demographics;[4] 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.[5] The dataset also included information from Washington State Unemployment Insurance wage records, which allowed us to control for students' working status and working hours in each term.

The system's dataset does not include courses dropped early in the semester (prior to the course census date, or the 10th instructional day after the quarter begins). After the

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

[5] The system divides course sections into three categories: face-to-face, online, and hybrid. Given that less than 2 percent of courses were offered in a hybrid format, and that these courses included a substantial on-campus component (i.e., online technology displaced at most 50 percent of the course delivery), we combined the hybrid and face-to-face formats in this analysis. In a robustness check, we excluded all hybrid courses from the analysis; the results are nearly identical to those presented in Table 1.1.s 1 through 4.

census date, students are not entitled to full refund if they drop the course. Those who choose to drop after that point receive a grade of “W,” indicating withdrawal. Thus, in our study, “course withdrawal” denotes that a student paid tuition for a course but officially dropped prior to the term’s end. “Course persistence” indicates that a student formally remained through the end of the term—although some may have informally chosen to desist work in the course and thus received a failing grade. Students who persisted in each course received a grade ranging from 0.0 to 4.0.[6]

The 34 Washington community colleges have widely varying institutional characteristics. The system comprises a mix of large and small schools, as well as institutions located in rural, suburban, and urban settings. Most colleges are comprehensive (offering both transfer-oriented and occupationally-oriented degrees), but five are technical colleges that primarily offer occupational degrees. Table 1.1.1 describes the 34 colleges’ institutional characteristics in fall 2004, based on statistics reported to the Integrated Postsecondary Education Data System (IPEDS) database. Compared to the national sample, Washington’s community and technical colleges are more likely to be located in urban areas and serve lower proportions of African American and Hispanic students, as well as lower proportions of students who receive federal financial aid.

2.2 Sample Description

A major assumption underlying the use of distance as an instrument (discussed further in section 3) is that students do not choose where to live based on unobserved confounding variables that influence both online enrollment and course outcomes. One such potential confounding variable is educational motivation, which may be particularly

[6] Each student’s grade is recorded to one decimal place.

relevant in the context of community colleges, given the wide variation in their students' educational intent (Alfonso, 2006; Alfonso, Bailey, & Scott, 2005). To address this concern, we focused on in-state students enrolled in an academic transfer-oriented track (*N* = 22,624), who intended to eventually transfer to a four-year school and earn a bachelor's degree. Among these students, 95 percent lived within 65 miles of their college, with an average distance of 17 miles.[7]

Because our goal was to understand the impact of online versus face-to-face delivery *within* specific courses, we excluded courses where all sections were offered through the same delivery format. That is, all courses in our analysis were offered through both online and face-to-face sections. In addition, we excluded developmental education (or "remedial") courses, given that very few of them were offered online. Finally, a handful of courses (less than 0.003 percent) were taken at a school that was not the student's primary college, raising the concern that distance could be endogenous in these cases. To be conservative, we dropped those courses from analysis.[8]

The final analysis sample included 125,218 course enrollments among 18,567 students; approximately 22 percent of enrollments were in online sections. Student summary statistics are displayed in Table 1.1. 2. In addition to the statistics for the full student sample (column 1), the Table presents the characteristics of students who ever attempted an online course across the five-year period of study ("ever-online" students, column 2) and the characteristics of students who never took an online course during that

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

[8] In a separate robustness check, we included those courses in the analysis, and the results were consistent.

period (column 3). On a descriptive basis, it appears that the ever-online student population was comprised of larger proportions of females, White students, students of higher socioeconomic status (SES), students who applied and were eligible for need-based aid, students who lived slightly farther away from their college of attendance, and students who worked more hours in a term. The ever-online student sample also seems to have had a higher level of academic preparedness; larger proportions of ever-online students were dual enrolled prior to college, and ever-online students had higher grade point averages (GPA) and had earned more credits by the end of their first term.[9] These statistics imply that students with stronger academic preparation were more likely to attempt an online section of a given course. However, it is also possible that more prepared students tended to take courses in certain subjects that also happened to have more online sections. To account for this possibility, we used academic subject fixed effects to control for student self-selection into different subject areas (see section 3.1 for details).

2.3 Online Courses in Washington Community and Technical Colleges

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

[9] Although first-term GPA provides a useful sense of students' initial academic performance, it could be affected by students' choices of online versus face-to-face formats during their first term. However, less than 13 percent (*N* = 2,376) of our sample took an online course in their first term, and when we excluded these students from our analysis, the academic advantage in first-term GPA persisted for ever-online students.

on the online course management system and voluntary training on effective online pedagogies, advanced technological tools, and other topics).

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

Across the five-year period of the study, online course-taking increased substantially. In the fall of 2004, entering students attempted an average of 1.03 credits online (12 percent of their term credits); by the spring of 2009, still-enrolled students in the 2004 cohort had more than doubled their rate of online credit attempts to an average of 2.56 credits (39 percent of their term credits). This growth was due to two separate trends. First, students in the 2004 cohort were increasingly likely to try at least one online course over time. Second, among only students who were actively online in a given term, the percentage of credits taken online also increased across terms. To account for growth over time, we include controls for term-level variation in our analysis.

3. Method

3.1 Basic Empirical Model

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

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

In this equation, *online* is the key explanatory variable and is equal to 1 if the course is taken online. We incorporated a rich set of controls into our model, where X_i includes demographic attributes (e.g., age, gender, race, SES), academic preparedness (e.g., remedial status, previous dual enrollment), and semester-level information (e.g., working hours in current term, total credits taken in current term).[10] In addition, we included fixed effects for the term of enrollment in the course (π_t), the subject of the course (ρ_k), and the campus of attendance (σ_j).

3.2 Addressing Between-Course Selection Using a Course Fixed Effects Approach

By including college, term, and course subject fixed effects, Equation 1 addresses two potential problems related to student selection of online courses. First, students may

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

choose course subjects based on their preference for online or face-to-face course formats. For example, if a campus offers sociology but not psychology online, then a student who prefers to take online courses may choose to fulfill his or her social science requirement with the online sociology course rather than the face-to-face psychology course. Second, online courses may be more prevalent within particular colleges, terms, departments, or course subjects. Thus, for example, students enrolled in an English program may be more likely to enroll in online courses than those in an engineering program.

Although Equation 1 addresses these issues, it cannot account for a potential third problem: Certain courses (even within a particular college, term, and subject) may be more likely to be offered online. For example, suppose that within a given department, advanced courses were more likely to be offered online than entry-level courses. A direct comparison of online and face-to-face sections across these courses would then result in biased estimates. To address this problem, we used estimated an additional model that used course fixed effects in addition to using college, term, and subject fixed effects, thus effectively comparing online and face-to-face sections of the same course. [11]

3.3 Addressing Within-Course Selection Using an Instrumental Variable Approach

Although course fixed effects are an effective means of controlling for student self-selection into different courses, there may be some remaining selection issues if students systematically sort between online and face-to-face sections of a single course. To deal with this concern, we employed an IV approach, using a variable related to the treatment but theoretically unrelated to the outcome to identify the treatment effect. In this analysis, we used the distance from each student's home to their college campus as an

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

instrument for the student's likelihood of enrolling in an online rather than face-to-face section. Specifically, we first identified the associated geocode for each address in the dataset, including both student home address and college address; we then used Google Maps to calculate the "travel distance" between each student's home and their college of attendance. Given that online courses offer the flexibility of off-site education, students who live farther from their own college campus might be more likely to take advantage of online courses, compared with students who live closer to their college. Using distance as an instrumental variable, we modified Equation 1 to use an IV approach. Specifically, we first predicted the probability that an individual *i* took a particular course *c* online using a probit model:

$$\text{Prob}\,(online_{ic}) = \Phi\,(\alpha + \delta distance_i + \gamma\, X_i + Z_c + \mu_{ic}) \qquad (2)$$

where Φ represents the cumulative density function for the standard normal distribution. Consistent estimates of the relative impact of online delivery format can be then derived by using the estimated probabilities from Equation 2 as instruments for the endogenous dummy variable $online_{ic}$ in a 2SLS estimation process.[12]

There are four potential concerns with using distance as an instrument. First, researchers (e.g., Long & Kurlaender, 2008) have argued that distance may be a problematic instrument when using national datasets because of differences in the way distance is perceived across the country. This concern is limited in the current context, given that we focused on one state; in our sample, the average distance from a student's home to the college of attendance was 17 miles, with nearly 90 percent of students living

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

within 25 miles. It is unlikely that perceptions of distance would be fundamentally different within such a small range. In addition, given the mountainous terrain in Washington State, where short distances may translate into long commutes, we used travel distance rather than direct-line distance.

Second, one might be concerned about two endogeneity issues. Some researchers have suggested that individuals or families who value education might choose to live near a college campus (e.g., Card, 1995; Long & Kurlaender, 2008; Rouse, 1995), although we have addressed this concern to a certain extent by limiting the sample to students who were enrolled in an academic transfer-oriented track (as opposed to a career-technical track) and thus were relatively homogeneous in their educational intent. In addition, proximity to college might directly affect student course outcomes, rather than merely affecting them indirectly through the online treatment. To address both concerns, we conducted a falsification test by assessing the relationships between course outcomes and distance for a sample of face-to-face courses (see section 4.3).

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

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

4. Results

4.1 Ordinary Least Squares Estimates

In descriptive terms, across the total sample of 125,218 course enrollments the overall course persistence rate was 93 percent, with a gap between online courses (91 percent) and face-to-face courses (94 percent). For enrollments that persisted until the end of the semester (N = 116,830), the average grade was 2.65 (on a 4-point scale), also with a gap between online courses (2.54) and face-to-face courses (2.68).[13]

Table 1.1.3 presents baseline probit and OLS estimates of the relationship between online course format and the outcomes of course persistence and course grade. The regression includes the vector of student characteristics X_i but does not include any fixed effects. The results suggest that the online course format had a significant negative relationship with both course persistence and course grade. Converting the probit coefficient (β = -0.257) for course persistence to a marginal effect[14] indicates that online course persistence rates were 3.6 percentage points lower than face-to-face persistence rates. Among students who persisted through the course, the average grade in online courses was approximately 0.19 points lower than in face-to-face courses.

[13] Please see the bottom panel in Table 1.1.2 for the standard deviation of each outcome variable by course delivery format.

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

Table 1.1.3 also shows the estimated coefficients for the controls in the model. Overall, women, full-time students, older students, and those eligible for financial aid tended to perform better academically, while ethnic minority and low-income students and those working more hours per week tended to perform worse.

The left panel of Table 1.1.4 contrasts the baseline estimates for online learning with the estimates from the fixed-effects models. When fixed effects for college, course subject, and term were included (column 2), the estimated negative relationship became larger for both outcome measures; when course fixed effects were included (column 3), the gaps between online and face-to-face outcomes were further magnified to −4.4 percentage points for course persistence and −0.26 grade points for course grade.

4.2 Instrumental Variable Estimates

To control for selection into online coursework based on unobservable student characteristics, our IV strategy used the distance between a student's home and college of attendance as an instrument for the likelihood of enrolling in an online rather than face-to-face section of a particular course controlling for all other available covariates. Table 1.1.5 shows the first-stage results using Equation 2 and indicates that distance between a student's home and college is a significant and positive predictor of online enrollment across all models. We conducted *F*-tests on the excluded instrument to test its strength,[15] and our results indicated that distance does indeed help explain which students choose

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

online course sections after controlling for all other covariates, no matter which model specification is employed.

However, for the IV estimates to be consistent, it must also be the case that distance is uncorrelated with the error term. As noted earlier in the paper, it is possible that those who value education might choose to live closer to a college campus, or that students living closer to campus might perform at a higher level due to easy access to college facilities and instructors. Either scenario would result in a correlation between the instrumental variable and the error term.

To assess the extent of this potential problem, we conducted an exploratory analysis in which we excluded all online courses from the sample and examined the relationship between course outcomes and distance for the subsample of face-to-face courses.[16] If students living farther from campus were systematically less motivated or encountered greater inconvenience in accessing school resources, then distance would be directly related to course outcomes for this subsample. The results of this exploration (see Table 1.1.6), which are robust to all model specifications, suggest no relationship between course outcomes and distance for face-to-face courses. This evidence of independence strengthens our interpretation that the IV estimates reflect the impact of course delivery format on course outcomes.

The right panel in Table 1.1.4 shows the IV estimates for online learning in terms of each course outcome measure. The results echo the OLS estimates: The online course format had a negative estimate for both course persistence and course grade, and the impacts became stronger when we added fixed effects. In addition, the IV estimates are

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

noticeably and consistently stronger than the corresponding OLS estimates using each model specification. For course persistence, the marginal effect derived from the IV estimate controlling for all fixed effects (column 6) is −0.07, compared with −0.04 based on the OLS model. For course grade, the column 6 estimate is −0.43, compared with −0.27 based on the OLS model. The magnification of the estimates after controlling for both observed and unobserved characteristics supports the notion that online courses are more popular among more motivated and academically better prepared students. As a result, straightforward OLS estimates may be subject to a downward bias when precise measures of academic ability and motivation are unavailable.

4.3 Robustness Checks

Given that the colleges in our sample varied widely in terms of their enrollment sizes and in the proportion of course enrollments that were online, we conducted two robustness checks to ensure that our results did not reflect the effectiveness of online courses in particular schools. We reran analyses based on a sample excluding the three colleges with the largest student enrollments, as well as on a sample excluding the three colleges with the largest online enrollments. Despite small variations, the results were similar to those presented in Table 1.1.4.

Another potential concern is that our results may be driven by a small set of individuals who took an entirely online curriculum or a high proportion of courses online. Yet among the 18,567 students in the sample, only 3 percent (N = 574) took all of their courses online; most students who attempted online courses enrolled in them intermittently, or as one course among several face-to-face courses. In addition, the majority of “fully online” students took no more than three online courses before they dropped out from the college. The courses taken by these students (N = 1,778) make up only 1 percent of the full course sample, and thus should not exert a large impact on the estimates. As a robustness check, however, we excluded all fully online students from the sample, and the results were nearly the same as those presented in Table 1.1.4.

In a similar vein, we considered the possibility that our results were driven by a few large courses that offered a high number of online sections. To address this concern, we restricted the data to courses in which at least 30 percent of enrollments were in face-to-face sections (N = 120,066) and reran the analysis on this subsample. Despite minor variations in the coefficients, the results were qualitatively similar to those presented in Table 1.1.4.

A final concern with our analysis is that we relied primarily on a cohort that entered college nearly a decade ago, in 2004. The advantage of examining this cohort is that it supplies several years of data for each student, making the course fixed effects strategy more plausible. The disadvantage is that online course technologies may have evolved since these students entered college, resulting in improved outcomes vis-à-vis face-to-face courses. To investigate this possibility, we examined changes over time in course outcomes. Descriptive data shown in Figure 1.1.1 suggest that although course outcomes varied over time, the gap in performance between online and face-to-face outcomes remained fairly consistent. To conduct a more explicit test of whether the gap remained consistent, we added interaction terms between year dummies and online format into the model shown in column 6 of Table 1.1. 4. We used an F-test to examine the joint statistical significance of these interaction terms; the null hypothesis—that they were jointly insignificant—failed to be rejected for either course persistence (F = 1.22, p

= 0.25) or course grade (F = 0.25, p = 0.89). That is, the adjusted association between course format and student performance did not change significantly over the four-year span of the study, suggesting that evolving technologies either were not adopted or did not have a strong impact on online success.

5. Discussion and Conclusion

Using a unique dataset with information on a large and representative set of online courses and similar face-to-face courses, we explored the impact of online delivery on student course performance in the community college setting. Estimates across all model specifications suggest that the online format had a significant negative impact on both course persistence and course grade. This relationship remained significant even when we used an IV approach and course fixed effects to address within- and between-course selection. In practical terms, these results indicate that for the typical student, taking a particular course in an online rather than face-to-face format would decrease his or her likelihood of course persistence by 7 percentage points (e.g., from 95% to 88%), and if the student persisted to the end of the course, would lower his or her final grade by more than 0.4 points (e.g., from 2.85 to 2.42).

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

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

Second, some colleges may be more thoughtful than others in terms of how they design and support online courses. Well-regarded online courses are often designed through a team-based approach, with faculty collaborating with an instructional designer and often with additional support staff (Alvarez, Blair, Monske, & Wolf, 2005; Hawkes & Coldeway, 2002; Hixon, 2008; Knowles & Kalata, 2007; Puzziferro & Shelton, 2008; Thille, 2008; Xu & Morris, 2007). High-quality online courses may need to be designed to promote strong interpersonal connections, which a large body of empirical research suggests is important to students' motivation, engagement, and academic performance in the course (Bernard et al., 2009). Effective online teaching may also require explicitly developing students' time management and independent learning skills, which are thought to be critical to success in distance and online education (e.g., Bambara, Harbour, Davies, & Athey, 2009; Bork & Rucks-Ahidiana, 2013; Ehrman, 1990; Eisenberg & Dowsett, 1990).

The extent to which the typical college supports its faculty in designing and teaching high-quality courses is unknown. Most community college systems, such as that in Washington State, have already expended substantial resources to support online learning. However, most of these supports are provided on a passive basis rather than proactively integrated into the everyday activities of students and faculty,[17] as recent research suggests is necessary in order for such supports to have sustained effectiveness (Karp, 2011). In particular, studies in the community college setting suggest that most faculty are left to design online courses on their own and keenly feel a lack of training and ongoing support (Cox, 2006; Millward, 2008; Pagliari, Batts, & McFadden, 2009).

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

Despite the negative results of our study, we acknowledge that online learning is an important strategy to improve course access and flexibility in higher education, with benefits from both the student perspective and the institutional perspective. From the student perspective, the convenience of online learning is particularly valuable to adults with multiple responsibilities and highly scheduled lives; thus, online learning can be a boon to workforce development, helping adults to return to school and complete

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

additional education that otherwise could not fit into their daily routines. From an institutional perspective, online modalities allow colleges to offer additional courses or course sections to their students, increasing student access to (and presumably progression through) required courses. Given the value of these benefits, online courses are likely to become an increasingly important feature of postsecondary education. The results of this study, however, suggest that colleges need to take steps to ensure that students perform as well in online courses as they do in face-to-face courses, before continuing to expand their online course offerings.

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

Section Two: Performance Gap Between Online and Face-to-face Delivery Format: Differences Across Types of Students and Academic Subject Areas

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,[18] 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 greater challenge for many, which may lead to performance gaps between distance learning and traditional face-to-face learning. In this paper, we define such potential performance gap between online and face-to-face learning as student "adaptability" to the online learning context.

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.

[18]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.

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 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[19] 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. Although the empirical strategy enabled us to effectively isolate the causal impact of alternative delivery formats on student performance, the sample constraints imposed by

[19]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.

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[20] in one of Washington State's 34 community or technical colleges during the fall term of 2004. These first-time college students were tracked

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

through the spring of 2009 for 19 quarters[21] 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.

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[22] 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,[23] course delivery format,[24] and grade earned in the course (ranging from a

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[21]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*.

[22]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.

[23]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 1.2.2 using the CIP codes by 2-digit series.

[24]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 Table 1.2.2 to 1.2.5.

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 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 1.2. 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.

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:

$$Y_i = \alpha_i + \beta\, online_i + \gamma\, X_i + \mu_i \qquad (1)$$ [25]

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

[25]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 1.2.3. We present the results from OLS estimates for easier interpretation.

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:

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

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:

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

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:

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

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 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 1.2.3 (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 1.2. 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).

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 1.2.3 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.

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)[26] 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

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[26]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.

individual variables (that is, to *overestimate* students' abilities to positively adapt to online learning).

On the right side of Table 1.2.3, 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[27] 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 1.2.4. As a first step in each heterogeneity analysis, we included an overall interaction term between the given individual attribute and course format into 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

[27]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.

necessary to interpret the main effects of student characteristics, we conducted supplemental analyses using Equation 1.[28]

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

[28]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.

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 1.2.4 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.[29] 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 took all their courses online in that term (3 percent). As shown in Table 1.2.4, 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

[29]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 1.2.3 (e.g., estimates based on model 3 are $\text{coefficient}_{\text{persistence}} = -0.046$, $p < .01$; $\text{coefficient}_{\text{grade}} = -0.275$, $p < .01$).

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 1.2.4: 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,[30] and examined the joint significance of all the interaction terms through an *F* test. The interaction test was

[30]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 1.2.2.

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 presented in Table 1.2.5, 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 1.2.2).

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 1.2. 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; $\text{Coefficient}_{\text{persistence}} = -0.050$, $p < .01$; $\text{Coefficient}_{\text{grade}} = -0.195$, $p < .01$) and applied professions (N = 12,924; $\text{Coefficient}_{\text{persistence}} = -0.020$, $p = 0.01$; $\text{Coefficient}_{\text{grade}} = -0.135$, $p < .01$).

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 1.2.2, 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.

Chapter Two: Examining the Impact of Adjunct Instructors on Student Current and Sequential Course Outcomes within a Community College System: An Instrumental Variable Approach

1. Introduction

In the past three decades, one of the most pronounced trends in higher education has been a steady increase in the use of part-time adjunct college faculty[31]. According to the national Center for Education Statistics (NCES, 1990, 2005), the use of part-time instructors was 33 percent in 1987; the number rose to 44 percent in 2003, representing a 33 percent increase. This pattern is particularly pronounced at two-year public institutions: the ratio of full-time to part-time faculty, roughly a 2:1 percent ratio before 1970, has reversed to 1:2 in 2003 (NCES, 2001, 2008), with some community colleges reporting closer to 80 percent part-timers (Balch, 1999).

While part-time faculty, most often visiting scholars and skilled professionals, were traditionally employed to enhance the quality and prestige of institutions and bring skills and talents that makes a complement to those possessed by the regular faculty (Jacobs, 1998), the nature of their use has changed as the percentage has experienced a surge: administrators in many colleges have increased the proportion of adjunct instructors as convenient and expedient means to lower costs and increase flexibility for institutions, as the costs saved from hiring adjunct instructors are potentially huge (Rhoades, 1996; Gappa & Leslie, 1997; Wagoner, Metcalfe, & Olaore, 2004). Part-time faculty in 2003 on average earned $2, 836 per course compared to $10, 563 per course for full-time faculty in all community colleges (National Education Association, 2007); the

[31] This study uses the convention definition of adjuncts as part-time faculty. Therefore, adjuncts and part-time faculty are used interchangeably throughout the paper.

cost difference is even wider considering that adjunct faculty typically receive minimal benefits from the college (NCES, 2001). In addition, given the difficulty and increased price for employers to terminate tenure full-time faculty (Ehrenberg, 2002), temporary adjunct instructors become more appealing to institutions for its flexibility and save on labor costs.

Yet, the increased teaching role of part-time faculty in colleges has been under the radar of the public critique. Though varied in focus, much of this scholarship makes the tacit assumption that overreliance upon part-time faculty employment may harm student success. The American Association of State Colleges and Universities (1999), for example, cautions that "because of its potential to adversely affect institutions, the extensive use of part-time faculty should be carefully re-examined as part of a larger re-examination of appropriate faculty mix" (p. 24). Skeptics of part-time faculty employment have listed several potential disadvantages of adjunct instructors compared to full-time counterparts: adjuncts typically do not have terminal degrees (e.g. Ph.D.s) and as a result may lack subject-matter expertise (Leslie, 1998). Due to low compensation, minimal benefits, and absent job security (Adamowicz, 2007; Friedlander, 1980; Jacoby, 2005; Schmidt, 2008), part-timers at community colleges were found to hold "scant loyalty for the institution and an increasing sense of frustration with their circumstances" (p. 68, Brewster, 2000), which, in turn, may negatively impact the quality of instruction and their interactions with the students.

Despite the widespread public concerns about the overreliance of part-time faculty on student learning outcomes, however, there is very little hard evidence regarding the relative impacts of adjunct instructors on student academic outcomes in higher education.

Although some researchers explored potential differences between part-time and full-time faculty in their approach to instruction and interaction with students (e.g. Benjamin 2002, 2003; Schuetz, 2002; Umbach, 2007), they did not link the type of instructor to student academic outcomes. Among the studies that directly measure adjuncts on student outcomes, the majority relied on aggregated data (e.g. Bettinger & Long, 2006; Ehrenberg & Zhang, 2005; Jacoby, 2006) and had minimal controls of student self-sorting between instructors. While a handful of studies have made an initial step toward exploring the causal impact of adjuncts (e.g. Bettinger & Long, 2010; Carrell & West, 2010) using experimental or quasi-experimental designs, the generalizability of the results are often limited due to the particular characteristics of the educational setting examined and outdated data.

This paper intends to provide an updated comprehensive examination of the relative impacts of adjunct instructors on a comprehensive set of student academic outcomes in the particular setting of community colleges, including both contemporaneous outcomes (i.e. student course completion, which is further decomposed into course persistence and course grades) and follow-on outcomes (i.e. probability of taking additional courses, total cumulative subsequent course credits, and subsequent course completion). Based on a large administrative data set from a large community college system, I use course fixed effects to compare students who took the same course but were enrolled in sections with different instructors; to address within-course selection bias, I further use the semester-by-semester variation in the proportion of course sections offered by adjuncts in a particular college as an instrument for a student's likelihood of taking the course with an adjunct instructor.

The analyses, discussed in more detail below, show robust estimates of positive impacts of adjuncts on contemporaneous course outcomes but negative impacts on subsequent course performance. Additional analysis by subjects also reveals strong heterogeneous effects, where the negative impacts associated with adjuncts on subsequent course outcomes are stronger in subject areas that are more closely tied to an occupation.

These results therefore make several important contributions to the existing literature on adjuncts in higher education: First, using data from a large community college system, this study has updated and complemented the current literature by shedding light on the impacts of adjunct instructors on a previously unstudied educational context. Given the particularly important role of adjuncts in two-year colleges in an era of increasing costs associated with higher education and limited funding available, the results provide key information to college administrators who are contemplating the potential pitfalls and benefits of reliance on adjunct instructor. Additionally, with the unique panel data structure, the current study is able to explore a broad set of student outcomes, including both contemporaneous and subsequent academic performance, therefore offering a comprehensive understanding of the relative impacts of adjuncts on student current and follow-on academic performance. Finally, the results of this study echo those in Carrell and West's (2010) research, which explores the relationship between instructor quality and student course outcomes through a random assignment design in the United States Air Force Academe (USAFA). While the random assignment design strengthens the internal validity of that study, the empirical setting of the study limits its generalizability to other higher education contexts. Therefore, the close resemblance of findings in the current study provides additional support to their claim that less qualified instructors may be less capable of preparing students for follow-up studies due to limited capacity in broadening the curriculum, enhancing deeper understanding of content, or cultivating good study habits in students.

The remainder of this paper is organized as follows: section 2 reviews existing literature on the impacts of adjunct instructors in higher education; section 3 describes the sample; section 4 introduces the empirical strategies; section 5 presents the results based on both OLS and IV models; and section 6 discusses the implications of the findings.

2. Literature Review

Earlier studies comparing the effectiveness of part-time to full-time faculty have typically used student evaluations as a measurement of teaching quality and essentially demonstrated no difference of student evaluations on part-time and full-time faculty (Hellman, 1998). However, the counter argument is that undergraduate students, particularly those in their first two years of academe have little skills in determining the quality of faculty, and that student evaluation instruments for faculty are not inherently designed to be comparative and are of little use for this type of analysis (Leslie & Gappa, 2002). In addition, differences have been found in grading patterns, with par-time faculty grades being significantly higher (McArthur, 1999). This difference in grading may be explained by asserting that the job insecurity that comes with part-time employment may diminish an instructor's willingness to enforce exacting grade standards, as low grades have been shown to be inversely related to positive student evaluations (Sonner &

Sharland, 1993; Greenwald & Gilmore, 1997). As a result, student evaluation or contemporaneous course grade alone would not serve as appropriate outcome measure for assessing instruction effectiveness of faculty.

Consistent with this reasoning, some researchers (Benjamin, 2002, 2003; Schuetz, 2002; Umbach, 2007) have directly explored potential differences between part-time and full-time faculty in their approach to instruction and interaction with students. Benjamin (2002, 2003), for example, suggested ways that overreliance on part-time faculty may undermine successful student integration. Not only did he find that part-time faculty in general has reduced office hours and uses less technology in class, but he also found that many used less challenging instructional methods, including less use of nontraditional exam techniques, and lower writing expectations. Based on surveys of more than 1,500 faculty respondents from over 100 community colleges nationwide, Schuetz (2002) also found substantial differences between part-time and full-time faculty in terms of both teaching methods and extracurricular involvement with students, colleagues, and institutions. Specifically, she found that part-timers tend to “have less total teaching experience”, “use less innovative or collaborative teaching methods, and interact less with their students, peers, and institutions”; they also tend to “express less knowledge of students’ need for or use of support services” (p.44, Schuetz). Based on these findings, she concluded that students are unlikely to receive the same quality of instruction from part-time faculty in community colleges.

While successfully raising questions about the instructional effectiveness of part-time faculty in higher education, none of these studies directly link the type of instructor to student academic outcomes, thus failing to provide quantitative evidence to address the central question of whether heavy reliance on part-time faculty indeed significantly alters student outcomes. This issue was directly assessed in some more recent quantitative studies using regression techniques based on institutional-level or individual-level aggregate data (Bettinger & Long, 2006; Eagan & Jaeger, 2009; Ehrenberg & Zhang, 2005; Harrington & Schibik, 2001; Jacoby, 2006; Jaeger & Eagan, 2009), generally observing a negative correlation between reliance on adjunct instructors and aggregated student outcomes. For example, using data from Integrated Postsecondary Data System (IPEDS), Jacoby (2006) found that community college graduation rates decrease as the proportion of part-time faculty employed increases. Using individual semester-level aggregated data, Harrington & Schibik (2001) obtained similar results that, when freshmen took a higher percentage of their course with part-time faculty, they were less likely to persist towards their degree.

With the increased availability of administrative course-level data, a few studies directly examined the potential association between the type of instructor and student course outcomes (e.g. Bvurgess & Sanuel, 1999; Carrell & West, 2010; Hoffmann & Oreopoulos, 2009), and these studies generally observed a negative correlation between adjunct instructor and student preparation for subsequent learning. Bvurgess and Samuel (1999) compared the academic performance and retention of students enrolled in sequential English and mathematics courses, with either part-time or full-time professors. The results indicate that in both developmental and regular classes, community college students taking their first course from a part-time instructor were under-prepared for the second course. However, since students self-select into courses with different types of instructors, it is difficult to judge whether simple controls of individual characteristics can yield unbiased estimates of the causal impact of adjuncts on student course outcomes.

To address student selection issues, some researchers have used experimental or quasi-experimental designs to isolate the causal impact of alternative instructors. Carrell and West (2010) used a course-level data set from the United States Air Force Academy (USAFA) where students are randomly assigned to instructors over a wide variety of standardized core courses. They explored the impacts of instructors on both contemporaneous and follow-on course grades. The results show that characteristics of high quality instructors, such as higher academic rank, more teaching experience, and higher terminal degree status are negatively associated with student contemporaneous course outcomes but positively associated with subsequent course achievement. While the random design of Carrell and West's study provides convincing evidence regarding the positive relationship between instructor quality and student learning outcomes in higher education, it did not focus on the role of adjuncts; the particular student sample and academic setting in USAFA also limits the generalizability of the results to other higher education settings.

Only one study to date has used quasi-experimental design to directly assess the relative impact of adjuncts on college student academic outcomes. Based on administrative data set of over 43, 000 students who began at a public, four-year college in Ohio during fall 1998 or fall 1999, Bettinger & Long (2010) used the term-by-term changes in departmental faculty composition as an instrument for students' likelihood of taking a particular course with an adjunct rather than full-time instructor, and explored the impact of having an adjunct in their introduction to a particular subject on subsequent course taking behavior and eventual major choice. The results indicate that adjunct instructors have no impact or positive impact on student interest[32] in a subject, with larger impact observed in areas more closely tied to an occupation (e.g. education, business) as opposed to academic areas (e.g. mathematics, English).

While Bettinger & Long (2010)'s study has made an important step toward exploring the causal impact of adjuncts on student academic outcomes, the extent to which its results can be generalizable to the current community college setting requires further exploration. First, using data from the 1990s, Bettinger & Long (2010)'s study explores the role of adjuncts over 15 years ago. As Figure 2.1 shows, the share of part-time faculty in both four-year and two-year colleges have dramatically increased between 1988 and 2010 by approximately 15 percentage points. Therefore, the role and impact of adjunct instructors today may be substantially different from those in the 1990s. Additionally, as the proportion of adjuncts are noticeably and consistently higher in two-year colleges than the share of adjuncts in four year universities (Figure 2.1), the characteristics of adjuncts in these two distinct educational settings might also be different. Indeed, according to a recent report by the American Federation of Teachers (AFT), part-time faculty members at four-year universities are more than twice likely to have a Ph.D (33 percent) than faculty from two-year colleges (16 percent); as a result, the relative impacts of adjuncts to full-time faculty in four-year universities may not be the same as adjuncts in community colleges. Moreover, in additional the impact of adjunct instructors on student course taking behaviors, it is also of great policy importance to

[32] There were three specific subsequent outcome measures to measure the impact of adjunct instructor on student subsequent interest in a subject area: whether a student took additional course in the same subject area, the total number of subsequent credits accumulated in the same subject area, and whether the student chose this subject area as his college major.

explore the impact of instructors on course persistence and grades in both contemporaneous or follow-up courses.

Given the current size and increasing reliance on part-time faculty, the impact of alternative instructors on student academic outcomes are of crucial importance to policy makers, college administrators, and students. Review of the existing literature indicates a strong need for further research into this aspect of higher education. First, the majority of studies addressing the effectiveness of alternative instructors have none or minimal control of student background characteristics. As directly pointed out by Bettinger & Long (2010), simple comparisons of students with full-time faculty members to those with adjuncts are likely to be biased because students who take adjuncts differ systematically from other students. In addition, none of the prior studies has fully explored student course outcomes and academic interest in one study, therefore making it difficult to obtaining a comprehensive understanding of adjunct instructors at a given education setting. Finally, despite an increasing awareness that adjunct instructors can be heterogeneous in their goals and preferences when accepting a part-time teaching position (Rajagopal & Lin, 1996; Halfond, 2000; Conley & Leslie, 2002) and as a result may vary in their instructional quality and impacts on students (Bettinger & Long, 2010), very few attempts have been made to explore the potential heterogeneous impacts among adjuncts in different educational settings and across various subjects.

In view of the particularly important role of adjuncts in community colleges and scant evidence regarding their impacts, the current study intends to provide a comprehensive measurement of the impacts of adjuncts in the community college setting on a broad range of student academic outcomes, including contemporaneous course outcomes, follow-on course taking patterns, and subsequent course performance.

3. Data

3.1 Data and Institutional Characteristics

Analyses were performed on a dataset containing more than 27,000 students from a large community college system (referred to as LCCS hereafter). First-time students who initially enrolled during the summer or fall of 2007 were tracked until the spring of 2012, for approximately five years. The dataset contains information on student demographics, institutions attended, and each student's intended major at college entry. Additionally, it also includes transcript data on each course taken, grades received, course section number, course subject, whether it was a developmental or college-level course, whether it was a distance-education or face-to-face section, and whether it was taught by a full-time instructor or part-time adjunct instructor[33]. One great advantage of this data set is that students can be tracked across colleges within LCCS. Therefore, even if a student transfers to or takes courses in a college other than the one they started with, I am still able to note the subsequent course taking patterns and grades[34]. Students who dropped the course early in the semester (prior to the course census date) are not included in the dataset. Thus, in this dataset, a "dropout" student paid full tuition for the course but did not persist to the end of the course.

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[33] The data sets also include student placement test scores for reading, writing, and math. However, about one third of the students are missing each placement test score. Therefore, these variables are not included in the main analysis but are included in a separate robust check. Additional inclusion of the three variables does not qualitatively change the results.

[34] This community college system uses common course numbering. For example, ENG111 represents exactly the same course (College Composition I) across the system.

The 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. For example, the system contains a large multi-campus institution with a high proportion of minority students located in the suburbs of a major metropolitan area, but also contains several small, rural, predominantly White schools. Overall, however, this community college system seems to represent a rural, low-income, underfunded and African-American student population[35].

3.2 Outcome Measures

This study examines the impact of taking a course section with an adjunct instructor on both the current course outcomes and the impact on subsequent course taking patterns and performance. The analyses on current course outcomes explore the impact of adjunct instructors on students' successful completion of their introductory courses within a specific subject area, where successful completion is defined as earning a C or above in courses with letter grade assigned and receiving a pass in pass or fail courses[36]. I then separately explore the impact on early course withdrawal and the impact on course grade as a continuous variable (on a 0 to 4 grading scale with 0.3 intervals) among those who persisted to the end of the course. This sub-analysis intends to aid the interpretation of the impact of alterative instructor on current course outcomes by identifying whether

[35] This description is based on statistics reported to the Integrated Postsecondary Education Data System (IPEDS) database.

[36] Course withdrawal is coded as unsuccessful attempt in this analysis.

taking an introductory course with an adjunct instructor rather than full time instructor would influence early course dropout, grade distribution, or both.

Yet, results of current course performances alone are difficult to interpret. For example, a significant positive impact from taking introductory courses with adjunct instructors may either due to more effective instruction or simply grade inflation. Therefore, I extend the results of current course outcomes to further measure the impacts of alternative instructors in students' entry-level course in an academic subject areas on their subsequent course-taking behaviors and performance within the same subject area: whether the student took any additional course within the same subject area after the initial exposure, the total number of subsequent credits attempted in this area, and students' probability of completing the subsequent course with C or above within the same area.

3.3 Sample Description

Because the aim of this paper is to understand the impact of alternative instructors during students' initial exposure to a subject area on their current and later academic outcomes in the same area, the analysis focuses on the first college-level course taken by each individual student in a subject area that offered sections taught by both full-time faculty and adjuncts within a college[37]. Given that students usually take introductory (entry-level) courses during their initial exposure to a particular subject area, these courses are referred to as "introductory courses" hereafter. If a student attempts an "introductory course" multiple times, only his first attempt is kept.

[37] If a student's first course taken in a subject area did not meet this criterion, that course is dropped from the analysis. College-level Courses that can not be classified into a specific academic discipline, such as physical education (N=14,570) are dropped from the sample.

Among all the introductory courses, nearly 85% of the courses had variations in the type of instructor. The remaining 15% of courses where all the sections were taught by the same type of instructor in a college were therefore dropped from the sample. In addition, a handful of courses were taken at a school that was not the student's primary college. This raises the concern that students may enroll in another college to take a course with a particular type of instructor. However, in the dataset, students demonstrated a strong pattern to take all courses at their home college; less than 5% of the course sample was taken at a school that was not the student's primary college. These courses are kept in the main analysis; yet, in a separate robustness check, I exclude those courses and the results are not qualitatively different from those presented in Table 2.1 to 2.8.

The final analysis sample includes 144,024 course enrollments among 26,030 students[38]. Table 2.1 provides summary statistics of the data. The upper panel presents student-level characteristics. The panel in the middle uses information from each student's college transcript and summarizes characteristics of course sections taken by each student. In addition to the full college-level introductory course sample (column 1), I also divide the sample into courses taught by adjuncts and courses taught by full-time faculty, and present summary statistics for the two subgroups respectively in column 2 and column 3. Across all these introductory courses, about half are taught by adjunct instructors. Compared to course sections taught by full-time faculty, sections taught by

[38] For analysis on subsequent course outcomes and course taking patterns, I collapsed the data set so each student only had one observation in each subject area, which yields a total observation of 137,522. This is based on the concern that the same subsequent outcomes would be observed more than once for students who took multiple courses during their initial exposure to a field. For these students, the key explanatory variable "adjunct" is defined as the proportion of credits taken with adjuncts, and the instrument is the average proportion of sections taught by adjuncts weighted by number of credits.

adjuncts are less likely to be delivered through the online format, more likely to be taken by students with slightly lower credit load in the current semester, and have smaller class size on average.

Finally, the bottom panel of Table 2.1 summarizes key outcomes explored in the current study. In terms of contemporaneous course outcomes, 68 percent of all the attempts in introductory courses received C or above, with course sections taught by adjuncts slightly but significantly higher than those taught by full-time faculty. When separately examining course persistence and course grade as a continuous variable on a 0 to 4 grading scale, both outcomes slightly favor adjuncts. In terms of subsequent outcomes, however, students who took their introductory courses with adjuncts were significantly less likely to take additional course in the same field and took 0.5 fewer subsequent credits in the same field. Yet, students who had their introductory course with adjuncts were associated with similar probability of receiving C or above in the subsequent course as those who had their initial exposure with a full-time faculty (0.73).

While about half of the enrollments in introductory courses are with adjuncts, there are substantial variations across academic areas. Table 2.2 presents enrollment patterns across various subject areas. In addition to the statistics for the introductory course sample used in the current analysis (column 1), the table also presents the proportion of enrollments with adjuncts by subject areas across all the college-level courses as a comparison (column 2)[39]. Among the 11 subject-area categories examined, adjuncts are most actively involved in teaching health related courses, where nearly 60% of the enrollments in introductory courses were taken with adjuncts. Foreign language is the second largest category with 56% enrollments with adjuncts, followed by humanities

[39] Note though that only the introductory course sample is used for analysis in this study.

and arts, with approximately 55% and 53% of course enrollments with adjuncts respectively. In contrast, adjuncts are less involved in teaching technology (with only less than 39% of course enrollments with adjuncts) and math (with 40% of course enrollments with adjuncts). In addition, comparisons between the introductory course sample and full course sample indicates that while the proportion of courses taught by adjuncts are about the same between entry-level courses and the full college-level course sample overall, noticeably larger proportions of courses were taught by adjunct instructors in introductory courses within certain fields, such as health (59% vs. 52%), foreign language (56% vs. 52%), and natural science (48% vs. 46%). This pattern implies that adjunct instructors might be more actively involved in entry-level courses than in more advanced courses within certain subject areas.

3.4 Variations in Course Offerings by Adjuncts across College, Fields, Course, and Time

As the current study uses semester-by-semester fluctuations of sections offered by adjunct instructors within a single course in a college as an instrument for students' varying probability of taking the course with adjunct (see section 4.3 for details), this section describes potential sources of such variation and the extent to which the remaining variation may be random after accounting for observable variations by college, academic fields, course, and year.

<u>Institutional context</u>. Institutional context may affect course offerings by adjuncts. As Figure 2.2a shows, the average percent of course sections taught by adjuncts varies substantially by colleges, ranging from 35% to 64%. The impact by colleges may take effect on the proportion of course sections taught by adjuncts via at least three ways. First, faculty employment can be largely influenced by variations in school revenue, where colleges faced with greater financial constraint may be tempted to replace full-time faculty with adjuncts to save on costs. Additionally, decisions regarding the number and the type of faculty may also depend on college policies of resource allocation, particularly the amount allocated to faculty wages and salaries. Finally, larger student enrollments may drive colleges to hire more adjuncts, particularly when the supply of potential full-time faculty in the labor market does not meet the demand of the students.

Subject Area. Subject areas may serve as another important source of variation in course offerings by Adjuncts. Figure 2.2b displays the average percent of course sections taught by adjuncts across key academic fields. In line with proportion of enrollments with adjuncts by fields presented in Table 2.2, adjuncts are more likely to teach courses in humanities, health, and foreign language, where more than 60% of the sections are offered by adjuncts. In contrast, adjuncts are less involved in teaching courses in business, math, and technology. Such noticeable variations by field may be influenced by the funding available to a department, as well as by the supply of adjuncts in a particular field in the labor market. For instance, while adjunct remains an occupation with low salaries relative to alternative professions in industry overall, it may be especially unattractive to individuals in math, business and technology due to usually higher salaries and growing demand for skilled labor in these fields.

Course Characteristics. Specific characteristics of a course, such as class size, time of the course section, delivery format, and difficulty of the course, can also affect the probability that the course is offered by an adjunct rather than full-time faculty, even within the same college and the same department. As shown in Table 2.1, adjuncts are more likely to be assigned to classes with smaller size and to face-to-face classes rather than a distance class. Additionally, as some adjuncts might be skilled professionals who hold full-time job in other sectors, they may be more likely to teach course sections during particular time of a day, such as evening classes. Finally, since adjuncts are less likely to hold a doctorate or terminate degree, they may also be more actively involved in teaching entry-level courses than more advanced courses within certain fields, as shown in Table 2.2.

Year Finally, changes in faculty composition may largely depend on annual fluctuations in labor market conditions, federal and local funding to colleges, supply of full-time faculty members in the labor market, demand for higher education, and so on. As shown in Figure 2.1, the proportion of part-time faculty in two-year public colleges, though demonstrating an overall increasing trend between 1988 and 2010, fluctuates substantially over time.

All these potential sources of variations in faculty composition may result in particular trend in semester-by-semester fluctuations in the proportion of course sections offered by adjuncts. Indeed, Figure 2.3a shows variations in course offerings by adjuncts in this large community college system across semesters between 2007 and 2012. In general, it demonstrates a non-substantial but noticeable rising trend over time. To further examine whether there is obvious pattern in the type of instructor teaching courses, it is useful to remove the observable trend in colleges, fields, courses, and year. Table 2.3b shows variations in course offerings by adjuncts after adjusting for course[40] and year

[40] Note that course is created as a string variable that combines college, department and course number information (e.g. coll01ENG111, where coll01 denotes the college; ENG represents the department and

fixed effects, and it does not exhibit a clear trend or pattern in the types of instructors teaching courses across semesters. This observation suggests that semester-by semester variations in the proportion of course sections taught by adjuncts within a particular course in a given year may be generally random due to retirements, sabbaticals, hiring, and temporary shifts in enrollment.

4. Empirical Framework and Methodology

4.1 Basic Empirical Model

To assess the impacts of adjunct instructors on student learning, I explore two sets of outcomes: 1) student performance in the first course taken by each individual within a particular subject area (i.e. the probability of receiving a C or above in that course, the probability of early withdrawal from the course, and course grade among those who persisted to the end of the course), and 2) student subsequent course-taking behavior and course performance in the next course within the same subject area (i.e. the likelihood of attempting additional courses in this discipline, the total number of credits attempted after the initial exposure, the probability of receiving a C or above in the next course in the same subject area[41], the probability of early withdrawal from that course, and course grade among those who persisted to the end of the next course). Since students are most likely to start with introductory courses during their initial semester of exposure to a

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111 is the course number). As a result, controlling for course fixed effects would automatically control for college and subject area fixed effects.

[41] In cases where students attempted multiple courses in a subject during his second semester of exposure, the outcome variable is defined as the proportion of credits receiving a C or above during that semester in that subject area. The same way of calculation is applied to the outcome of early withdrawal and course grades.

subject area, the quality of instruction in these courses may have substantial impact on student interest and success in subsequent courses in the same subject area.

The basic strategy relates student *i*'s outcomes in subject *k* at campus *j* in semester *t* to the type of instructor that the student had during his initial exposure to this subject:

$$Y_{itkj} = \alpha + \beta \text{ adjunct}_{itkj} + \gamma X_i + \pi_t + \rho_k + \sigma_j + \mu_{itkj} \qquad (1)$$[42]

The key explanatory variable is the type of instructor with whom a student took the introductory course in a subject and is defined as one if the course was taught by an adjunct. In addition to the fixed effects for the semester of enrollment in the course (π_t)[43], the subject of the course (ρ_k), and the campus of attendance (σ_j), the model also incorporates a rich set of controls, denoted by X_i which includes the academic major a student is pursuing[44], student demographic attributes (e.g., age[45], gender, race), academic preparedness (e.g., remedial status, previous dual enrollment), semester-level information (e.g., total credits taken in this term), and course section-level information (e.g. number of total enrollments in the course section; whether the course section is online or face-to-face)[46].

[42] For discrete outcome variables (e.g. course persistence), I also used logistic regression as a robustness check for this analysis, with results similar to those presented in Table 2.2 and Table 2.3.

[43] In cases where a student took multiple introductory courses during his initial exposure, I randomly choose a course for course fixed effects for the analysis on subsequent outcomes.

[44] Each student was required to report the major program they intend to pursue upon college entry.

[45] Age is used as a continuous variable in the main analysis; in a robust check, I also use age dummies, where students are divided into three age groups based on their age at college entry (below or equal to 18, between 18 and 25, above 25) and the results are almost the same as the those from the main analysis.

[46] The full list of covariates include dummy variables for the academic major a student is pursuing, gender, race, receipt of federal financial aid, limited English proficiency, dual enrollment prior to college, whether the student enrolled in a remedial course, and whether the course is an online or face-to-face course.

4.2 Addressing Between-Course Selection Using a Course Fixed Effects Approach

By including college, semester, and course subject fixed effects, Equation 1 addresses the problem that courses taught by adjunct instructors may be more prevalent within particular colleges, semesters, or course subjects; thus, for example, students enrolled in a health related programs may be more likely to take courses with adjuncts than those in a math program. While Equation 1 can deal effectively with these issues, it cannot account for the potential problem that adjunct instructors may be more likely to teach certain courses even within a particular college, term, and subject. For example, suppose that within a given department, full-time instructors were more likely to teach more demanding courses than adjunct instructors. Although this problem has been partly addressed by focusing on courses that student took during their initial exposure to a subject, there may still be remaining variations in difficulty across these courses as well as the distribution of the type of instructor. If that were the case, a direct comparison between different instructors across these courses may result in biased estimates. To address this problem, I take advantage of the administrative data set which includes the course number information for each course taken by student, and further add course fixed effects into the model in addition to college, term, and subject fixed effects[47], thus enabling comparisons among different sections of the same course.

4.3 Addressing Within-Course Selection Using an Instrumental Variable Approach

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Continuous variables include the total number of credits enrolled in that term and total number of students enrolled in the course section. The model for course outcomes in the subsequent course in a particular subject also controls for the type of instructor in that course and the semester when the course was taken.

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

Although section 4.2 argues that course fixed effects are an effective means of controlling for between-course selection bias, there may be some remaining selection issues if students systematically sort between sections taught by different types of instructors within a single course. For example, adjunct instructors may be more likely to teach evening sections of a course and students with certain characteristics may prefer to take these sections to balance their busy daytime schedule. To deal with this concern, I employ an instrumental variable strategy (IV) approach. Under the IV approach, a variable related to the treatment but theoretically unrelated to the outcome is used to identify the treatment effect. In this analysis, I use the number of sections offered by adjuncts within a particular course in a college during a particular semester for the student's likelihood of enrolling in a section with an adjunct instructor rather than full-time faculty. In other words, I use the semester-by-semester fluctuations of sections offered by adjunct instructors within a single course as an instrument for students' varying probability of taking the course with adjuncts. The hypothesis is that the variations of the specific number of sections taught by adjuncts within a single course in a college are related to students' probability of taking the course with adjuncts but are not related to the error term. Using the proportion of sections taught be adjuncts in a given course during a given semester in a college, I modify equation (1) to use an IV approach:

$$Y_{itg} = \alpha + \beta\, \text{adjunct}_{itg} + \gamma\, X_i + \pi_t + Z_g + \mu_{itg}$$

$$\text{where: } \text{adjunct}_{itg} = \alpha + \delta \text{pctadjunct}_{tg} + \gamma\, X_i + \pi_t + Z_g + \mu_{itg} \qquad (2)$$

In Equation 2, X_i denotes the individual-, course-, and semester-level covariates; π_t and Z_g are time and course fixed effects respectively. The key explanatory variable $adjunct_{itg}$ is instrumented using $pctadjunct_{tg}$, the percent of sections taught by adjuncts in a given course Z_g during semester π_t.The coefficient β would thus represent a consistent estimate of the impact of course format on course outcomes – but only if $pctadjunct_{tg}$ is indeed an appropriate instrument.

There are two potential endogeneity issues related to the instrumental variable in the current context. First, although variations in course offerings by adjuncts do not exhibit a clear trend or pattern in the types of instructors across semesters after adjusting for course and year fixed effects (Section 3.4), I cannot entirely rule out the possibility that the proportion of sections offered by adjuncts may be related to variables that are not effectively controlled by observable student-level and section characteristics, and college, subject area, course, and time fixed effects. One of such potential threat is semester-by-semester variations in college or department financial situation that may influence both faculty compositions (IV) and student course outcomes. While college or subject area fixed effects can address variations in financial situation across colleges or fields, they are not able to effectively address variations across semesters within a college or department.

The other potential difficulty with the proportion of sections taught by adjuncts as an instrument is that faculty composition in a department might directly affect student course outcomes, rather than merely affecting them indirectly through the course enrollment. To address both potential concerns, I have conducted a falsification test by assessing the relationships between course outcomes and the instrumental variable for a subsample of courses taught by full-time faculty only (see details in section 5.3).

Additionally, the percent of sections taught by adjuncts in a given course will be effective as an instrumental variable only if it indeed has a substantial influence on students' probability of enrolling in the course with an adjunct instructor. I directly examine the strength of the instrumental variable with an F test in the next section.

5. Empirical Results

5.1 Current Course Completion

Among all the 144,024 introductory courses, the overall course completion rate[48] was 68%. After separating courses taught by different types of instructors, those taken with an adjunct instructor had a higher average success rate by 4 percentage points (70% vs. 66%). To aid the interpretation of this general impact, I then separately explore the impact of adjunct instructors on early course withdrawal and on course grade among those who persisted to the end of the course. The overall course withdrawal rate was 11%, with slight difference between those taught by adjuncts (10%) and those by full-time instructors (11%); yet, the difference is much noticeable in terms of course grades among those who persisted to the end of the course (N=128,331), where the average grade was 2.57 in courses taught by adjuncts, compared to 2.38 by full-time faculty. Therefore, on a descriptive basis, it seems that introductory courses taken with adjunct instructors are associated with better course outcomes.

[48] Successful completion is defined as earning a C or above in courses with letter grade assigned and receiving a pass in pass or fail courses; courses withdrawal are coded as unsuccessful attempt.

The left panel in Table 2.3 presents OLS estimates from Equation 1, which examines the relationship between the type of instructor and course outcomes. The baseline regression (specification 1) includes the vector of student, semester, and course characteristics X_i, but does not include any college, time, or course fixed effects. The results suggest that adjunct instructors are associated with significantly better course outcomes. Specifically, students taking courses with adjuncts are more likely to earn a C or above by 4.4 percentage point; when separately looking at course persistence and course grades, students are more likely to persist to the end of the course by 1.2 percentage points and for students who persist through the course, the average grade in courses taken with an adjunct is higher by approximately 0.2 grade points. Once accounting for differences across colleges, course subjects, and semesters with fixed effects (specification 2), the estimated positive relationship remain for all outcome measures; yet, after course fixed effects are added into the model (specification 3), the significant association between the type of instructor and course persistence disappears while the other two still remain.

While using course and time fixed effects addresses concerns that the faculty composition across courses may not be random, these fixed effects are sufficient only if students unsystematically choose their particular section within a course, conditional on observed covariates. However, as shown in Table 2.4, there is reason to suspect student sorting between instructors within a particular course: the probability of taking the first course in a subject area with an adjunct instructor is significantly correlated with student, semester, and course section-level characteristics, and many of these correlations remain ever after time and course fixed effects are controlled. Focusing on the results based on course fixed effects model (column 3), adjunct instructors are significantly more popular with older students, students who are not eligible for need-based financial aid and students who took fewer credits in the current semester. Additionally, sections taught by adjuncts also have smaller enrollments and are less likely to be an online section. These patterns suggest that students sort between different types of instructors in non-random ways even within a particular course.

To address additional concerns about selection, the instrumental variable strategy uses the proportion of sections offered by adjunct instructors within a single course in a particular college at a certain semester as an instrument for students' likelihood of enrolling in a section taught by an adjunct instructor. Table 2.5 shows the first stage results and indicates that the proportion of sections taught by adjuncts is a significant and positive predictor of probability of taking the course with an adjunct across all models. To examine the strength of the instrumental variable, I further conduct *F*-tests on the excluded instrument,[49] and the results indicate that the instrument does indeed help explain whether a student chooses to enroll in a course with an adjunct ($p<0.01$), no matter which model specification is employed.

The right panel in Table 2.3 shows the instrumental variable estimates for alternative instructors in terms of each course outcome measure, where each specification uses the first stage estimates with corresponding specifications. Although the estimates become slightly smaller, the IV results echo the OLS estimates: Adjuncts have a positive

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[49] The strength of the instrument can be directly assessed because both the endogenous covariate (type of instructor) and the instrument (proportion of sections offered by adjuncts within a particular course in a given semester) are observable (Stock, Wright, and Yogo 2002). A common rule of thumb for models with one endogenous regressor, as in the current case, is: the *F*-statistic against the null that the excluded instrument is irrelevant in the first-stage regression should be larger than 10.

estimate for course completion and this effect is mainly due to higher grades associated with adjuncts rather than higher persistence rates.

5.2 Subsequent Course-Taking Patterns and Success

In terms of subsequent course-taking behavior and success within a particular subject area[50], I focus on three major outcomes: whether the student took any additional course within the subject area after the initial exposure, the total number of subsequent credits attempted in this subject area, and students' subsequent course performance in the same subject area. For subsequent course performance, I first examine the overall impact on subsequent course completion and then separately explore the impact on course persistence and that on course grades to aid interpretation.

On a descriptive basis, the overall probability that students took any additional course within the same subject area after their initial exposure is approximately 43%. In contrast to the positive impacts by adjunct instructors on immediate course outcomes, students who had adjuncts during their initial exposure to a specific subject[51] had a lower probability of attempting additional courses in the same subject (41% vs. 45%) descriptively. Similarly, the average number of total attempted subsequent credits in the same subject is 2.83, with a higher average observed among those who had their initial exposure with a full-time instructor (3.08 vs. 2.55). In terms of subsequent course performance, the average probability of receiving a C or above in student's second

[50] For analysis on subsequent outcomes, I collapsed the data set so each student had only one introductory course observation for each subject area, which leads to a slightly smaller course sample (N=137, 522) than the actual number of introductory courses taken by students (N=144,024).

[51] For the summary statistics, students are regarded as taking the initial course with an adjunct instructor if they had more than half of the total initial credits with adjunct instructors.

semester of exposure to a subject area is 73% despite the type of instructor during initial exposure.

The left panel in Table 2.6 presents OLS estimates while the right panel presents the corresponding IV estimates. Considering that students who had their introductory course with an adjunct may be more (or less) likely to take subsequent course with the same type of instructor, which in turn may influence their subsequent course performance, all model specifications for subsequent course performance (course completion, course persistence, course grade) also control for the type of instructor in that course as well as the semester when that course was taken. In contrast to the positive impact of adjuncts on current course outcomes, the estimates of the impacts of adjuncts on subsequent student outcomes are consistently negative, though not all of the coefficients reach significance at the 0.05 level across different model specifications. Focusing on the IV estimates with course and time fixed effects (column 6), while students who had their initial exposure to a subject area with an adjunct instructor are equally likely to attempt at least one additional course in the same subject area, they earn 0.3 fewer total credits in that area after their initial exposure (p <0.05).

In terms of subsequent course performance based on the IV estimates with course and time fixed effects (column 6), students who had their introductory course taught by an adjunct were significantly less likely to successfully complete the subsequent course (i.e. to earn a C or above) in the same subject area by three percentage points (p <0.05) than those who had their introductory course with a full-time faculty; this negative impact on course completion is mainly due to the lower grades associated with adjuncts rather than persistence rates: while student who had their introductory course with an adjunct were equally likely to persist through the end of the subsequent course in the same area, they were subject to a lower course grade by approximately 0.1 points on a one to four grading scale (p <0.05).

These results, taken together with those on contemporaneous course outcomes suggest that adjunct instructors excel in promoting contemporaneous course performance, but are comparatively less effective in preparing students for follow-on learning in the same field. These results echo those in Carrell and West (2010)'s experimental study, which identified a positive impact of lower instructor quality on contemporaneous course outcomes but a negative impact on subsequent course performance. One potential explanation for this result is that adjunct instructors, due to job insecurity, might reduce the difficulty of course content, lower course expectation, or relax grading criteria to earn good student evaluation. While these measures can help students earn higher and potentially inflated grades in contemporaneous courses, they can be potentially harmful to students' preparation for follow-on learning in more advanced coursework.

Another possibility is that adjuncts, who on average are less likely to hold advanced degrees, may be less capable of helping students achieve deep understanding of the course content, evolve critical thinking, and form beneficial learning habit, which in turn, may negatively influence subsequent learning of more advanced content. A related possibility is that while adjuncts excel in imparting the knowledge in introductory courses, their less involvement in more advanced coursework and in curriculum design in some fields may limit their capacity in broadening the introductory course content to prepare students for follow-on learning. Indeed, as shown in Table 2.2, the proportion of adjuncts in entry-level courses is higher than the proportion in college-level courses overall in several subject areas. As a result, adjunct instructors may lack both the awareness and knowledge of how to integrate introductory course content into the full spectrum of learning.

5.3 Validity of the Instrumental Variable and Robust Checks

The validity of the IV identification strategy used in the current study rests on the assumption that the fluctuation of faculty composition in a particular course is a legitimate instrument for student probability of taking that course with an adjunct. Table 2.5 (the first-stage IV) indicates that the proportion of sections offered by adjuncts is significantly and positively related to enrollment with adjuncts. However, for the IV estimates to be consistent, it must also be the case that it is uncorrelated with the error term.

As briefly discussed in section 4.3, there are two potential threats to this instrument: first, fluctuations of faculty composition in a particular course may be influenced by a series of unobservable factors, particularly those that vary on a semester-by-semester basis within a college, which can not be effectively controlled by using course and time fixed effects. Additionally, faculty composition in a department might directly affect student course outcomes rather than merely through course instruction. For example, adjuncts might be less engaged in interactions with students; they may be less engaged with the department as well and thus over-reliance on adjuncts may undermine the campus learning climate.

Either of the two threats would result in a correlation between the instrumental variable and the error term. To assess the extent of the potential problem, I conduct an exploratory analysis in which I limited the sample to courses taught by full-time faculty only, and examined the relationship between course outcomes and the instrumental variable. If there are unobservable variables, such as semester-by-semester variations in college financial situation that influence both the fluctuation of faculty composition in a course and student outcomes, or if faculty composition can directly influence student outcomes rather than through the type of instructor teaching the course, then the instrument would be directly related to course outcomes for this subsample. The results of this exploration (Table 2.7) suggest that there is no relationship between any of the current or subsequent course outcomes conditional on the covariates and fixed effects (column 3). This evidence of independence strengthens the interpretation that the IV estimates reflect the impacts of adjunct instructors on current and subsequent course outcomes.

Given that colleges in the sample varied widely in terms of both their enrollment sizes and in the proportion of course enrollments with adjunct instructors, I conduct two robustness checks to ensure that the results do not reflect the impacts in particular schools. Specifically, I re-run analyses based on a sample excluding the 3 colleges with the largest student enrollments, as well as on a sample excluding the 3 colleges with the largest enrollments with adjuncts. Despite small variations, results are similar to those presented in Table 2.3 and Table 2.6.

In addition, a handful of courses were taken at a school that was not the student's primary college. Although these courses only take up less than 5% of the course sample, it still raises the concern that students may enroll in another college in order to take a course with a particular type of instructor. To address this concern, I excluded all the courses taken in a college other than a student's primary school and re-ran all the analyses. Despite small variations, the results are similar to those presented in Table 2.1 to 2.7.

A related concern is that students may also intentionally alter the timing of taking a course in order to be able to take the course with a particular type of instructor. For example, for a student who tries to avoid adjuncts, he might choose to take a course in another semester if all of the sections are taught by adjunct instructors in the current semester. To address this concern, I interact each course with the semester when the course was taken and add the course-by-semester fixed effects into the model as a robust check. The results are not qualitatively different from those presented in Table 2.3 and Table 2.6.

Finally, since some of the outcome variables are discrete, and potential analytic problems may derive from using linear regression as the model specification, I use a probit model as a robustness check for the relationship between alternative instructors and each discrete outcome. The estimates of the marginal effects based on the probit model do not substantively alter the interpretation of the estimates for course completion, course persistence, and follow-on course taking patterns presented in Table 2.3 and Table 2.6.

5.4 Heterogeneous Impacts across Subject Areas

In order to explore how the relative impacts of adjuncts vary by academic subject areas, I divide all the subjects into academic areas (e.g. natural science, humanities), and applied professional areas (e.g. business, education). I first run the analyses separately within the two large divisions, and then separately estimate the coefficient for adjuncts within the 11 subject areas using the IV model specification with course and time fixed effects controlled. Results are presented in Table 2.8, with each cell representing a separation regression analysis.

In academic fields, 49% of enrollments in introductory courses are with adjuncts, which is slightly higher than occupational fields by two percentage points. As Table 2.8 shows, a contrast is clear between academic subject areas and professional areas overall: For academic areas, while students taking an introductory course with an adjunct instructor are equally likely to have higher grades in that course as they are in professional subject areas, there is no difference in subsequent course enrollment or course performance in the same subject area. However, when it comes to areas more closely tied to an occupation, students taking their introductory courses with an adjunct are less likely to complete subsequent course in the same subject area by more than 3 percentage points; they also on average took 0.8 fewer additional credits in that area.

Looking by specific subject area, nearly all the areas closely tied to academics have non-significant estimates for subsequent course outcomes, except for social sciences, where students who took their introductory course in this area take approximately 0.2 fewer additional credits afterwards. Yet, even this effect is substantially smaller compared to the -0.8 overall estimates associated with all the subject areas closely tied to an occupation. Breaking down the occupational field into specific occupational areas, the majority of the estimates on subsequent course completion and total credits are significantly negative, indicating that the negative impact of adjuncts in occupational areas is a common pattern observed in most of the fields rather than a coincidence driven by a particularly strong estimate in one or two areas. Focusing on the subsequent course completion, the negative impacts of having the initial exposure with an adjunct is particularly strong in computer science, technology, and applied arts, where the estimates are at least twice the size of the average negative impacts among all the occupational areas.

While the negative impacts of adjuncts on subsequent course outcomes dominate areas closely tied to an occupation, there is one exception: students who had their initial exposure to the subject of public service (including education, administration, and library) are not only more likely to complete that introductory course with higher grades, but are also significantly more likely to attend at least one additional course by 12 percentage points and earn 1.6 more additional credits in the same subject area; among those who attempt additional course in that area, they are also more likely to complete their subsequent course by 12 percentage points compared to those who had their initial exposure to this subject area with a full-time faculty.

One potential explanation for the lack of negative impacts of adjunct instructors on subsequent credits attempted in academic areas is that most academic transfer-oriented students are only required to take one course in most academic subjects, as they work to finish the general education core courses. For example, many transfer-oriented students may take only one Sociology or Psychology course to fulfill the general education requirement, and wait to take additional courses in a particular field after they transfer to a four-year university. If that were the case, the type of instructor during the initial exposure to a subject area for transfer-oriented students would have little impact on subsequent course taking behaviors, as they tend not to take additional courses in a subject area anyway. However, this scenario is not a major concern: while students in academic fields on average attempted fewer subsequent credits in a specific subject compared to students in the occupational fields (3.7 credits), these students still on average attempted 2.4 credits in the same academic subject area after the initial exposure, which indicates that many students still continue to take additional courses in the same area after their initial exposure before they transfer to a four-year university.

Yet, to address potential bias introduced by data limitation in tracking course taking patterns by transfer-oriented student outside of the community college system, I separately explore the potential heterogeneous impacts of adjuncts on subsequent course taking behaviors among career-tech students only. In contrast to transfer-oriented students who may save many of their courses after transfer, career-tech students usually take all of their courses within the community college system. However, this separate analysis (Introductory course sample of 47, 973) reveals similar pattern of results: students with adjunct instructors in their initial exposure to an academic subject area attempted similar number of total subsequent credits in the same subject area (coefficient=-0.023; se=0.095), while the estimate for occupational areas is significantly negative for adjuncts and noticeably larger compared to the estimates among all students (coefficient=-1.911; se=0.573).

6. Conclusion

In order to understand the relative impacts of adjunct instructors on student academic outcomes in the particular context of community colleges, the current study analyzes student course taking behaviors and performance with a large swath of introductory and follow-on courses across key subject fields using a statewide community college dataset. To address student self-sorting between instructors, I use an instrumental variable strategy augmented by course fixed effects, therefore controlling for both between- and within-course selection bias. The results indicate that adjunct instructors have significant impacts on both contemporaneous and follow-on course outcomes. Yet, the impacts are opposite to each other: while having one's initial exposure to a subject area with an adjunct are on average associated with greater likelihood of completing the contemporaneous course with a higher grade, these students are less likely to complete the subsequent course in the same subject area. Probably as a consequence, although students are equally likely to attempt at least one additional course despite the type of instructor in students' initial exposure in a subject area, students who had an adjunct in their introductory courses on average accumulated fewer total additional credits after their initial attempt. Additional analysis indicates that the negative impacts of adjuncts on subsequent course performance are particularly strong in subject areas that are more closely tied to an occupation.

The consistent negative impacts of adjuncts on follow-on course completion rates observed across the majority of subject areas warrant policy attention: If this pattern holds true across community colleges in other states, it would imply that the continued increase and particular overreliance of adjuncts in two-year community colleges could harm the educational outcomes of its student population, many of whom are already disadvantaged academically or economically upon college entry. This partly explains the consistent findings based on aggregated data (e.g. Eagan & Jaeger, 2009; Jacoby, 2006;

Jaeger & Eagan, 2009) that community college student outcomes, such as graduation rates, decrease as the proportion of part-time adjunct instructors employed increases.

Yet, there is no definite answer as to the mechanism by which these effects may operate. One potential explanation for the current findings is that adjunct instructors, due to limited involvement with the curriculum design and in teaching more advanced course work may lack both the awareness and knowledge of how to integrate introductory course content into the full spectrum of learning; a related possibility is that adjuncts, who on average are less likely to hold advanced degrees, may be less capable of broadening the instruction of entry-level knowledge to deeper understanding of key concepts in the subject area. As a result, adjunct instructors may tend to stick to the regimented contemporaneous course content tested. While this practice may help students receive higher grades in the entry-level courses, they are less effective in preparing students for future learning in the same subject area. These possibilities suggest that colleges need to provide more training and support to adjuncts; it is also beneficial for colleges to integrate adjuncts more closely into the department and provide adjuncts with more opportunities to either teach or observe advanced courses offered by the department.

Yet, an equally possible explanation for the current results is that adjunct instructors, due to job insecurity, might reduce the difficulty of course content, lower course expectation, or relax grading criteria to earn good student evaluation. While these measures can help students earn higher and potentially inflated grades in contemporaneous courses, they can be harmful to students' preparation for follow-on learning in more advanced coursework. This type of story puts the validity of using student course evaluation as the sole or major criteria for evaluating instructional effectiveness in colleges, and highlights the necessity of employing additional measures of instructional quality to complement student course evaluation.

Chapter Three: Assistance or Obstacle? The Impact of Different Levels of English Remediation On Underprepared Students in Community Colleges

1. Introduction

While higher education in the US has expanded rapidly in the past two decades, many new college students arrive on campus lacking the preparation to successfully pursue their postsecondary education (Greene and Foster, 2003). The most common approach that colleges use to address this widespread phenomenon has been to provide students who enter college with weak academic skills the opportunity to strengthen those skills and bring them up to an adequate level for further college-level coursework, which is often termed as “remedial” or “developmental” education. Recent studies (e.g. Bettinger & Long, 2005) indicate that the bulk of remediation is provided by non-selective public institutions; indeed, four-fifths of public four-year colleges and 98% of community colleges provide remedial courses. A recent report by NCES (2003) shows that among entering freshman in fall 2000, 30% overall and 42% of community college students participated in remediation. As various researchers and education policy makers have noted (e.g. Bailey et al., 2010; Bettinger & Long, 2005; Calcagno & Long, 2008; Martorell & McFarlin, 2009), placement exams and corresponding remediation courses in reading, writing, and mathematics have become a central feature of US higher education, especially in community colleges.

Despite the extent of remedial education, however, there is considerable uncertainty surrounding the effectiveness of this tactic. Advocates of remedial education have noted the potential benefits of remedial courses in helping underprepared students develop strong academic skills thereby improving college performance (McCabe, 2003); yet, remediation can also have other unintended consequences. First, since remedial courses are populated by low-ability students, peer effects may offset positive instructional effects if having low-ability peers has a negative impact on individual academic outcomes (Martorell & Farlin, 2009). A related possibility is that assignment to remediation might trigger “stereotype threat” (Steel & Aaronson, 1995) by stigmatizing students. In addition, since credits earned through remedial courses do not count toward a degree, remediation also results in greater burden on students for earning a college degree, which may lead to undesirable academic outcomes such as delayed college completion or dropout.

Numerous studies have been carried out to explore the impact of remediation on students, which can be categorized into two major strands. The first strand, primarily conducted in the 1980s and 1990s and most often descriptive in nature, directly compared the academic performance between students who had received remediation and those who had not, and often observed negative results for the remedial students. However, these studies have been criticized for ignoring the inherent differences between remedial students and college-ready students, which, as a result, failed to rule out the possibility that remedial students might have performed even worse in the absence of remediation (Grubb, 2001; Boylan & Saxon, 1999; Levin & Calcagno, 2008; O’Hear & MacDonald, 1995). A second strand of more recent empirical studies (e.g. Bettinger & Long, 2005; Lesik, 2007; Calcagno & Long, 2008; Martorell & McFarlin, 2009) have used quasi-experimental designs to draw causal inferences about the impact of remediation. Although these studies vary in the findings regarding the impacts of remedial education, overall they conclude that remediation seems to have no strong positive effect. A major limitation of all these studies, however, is that their methodologies allowed them to draw inferences only for students scoring near the remediation assignment cutoff scores. Accordingly, the impact of remediation on students with the least academic preparation has been largely left unexplored. The primary evidence related to the impacts of remediation on these students comes from a set of studies (e.g., Perin & Charron, 2006; Bailey et al., 2010) that analyzed students' progression through the sequence of remedial courses. Many students who score very poorly on remedial exams are placed into courses that are at least two levels below college level, and these studies suggest that very few of these students ever complete the remedial course sequence, much less embark on a college-level academic curriculum. Only one recent study (Boatman & Long 2010) explored the causal impact of remediation on students with much lower levels of preparation. Using a regression discontinuity design to isolate the causal impact of remediation, Boatman & Long identified large negative effects on the margin of needing remediation but smaller and sometimes positive effects on students placed in lower level remedial courses. However, the study is limited to one cohort (2000) in one state (Tennessee), raising the question of whether the results would be replicated in other areas of the U.S. In addition, current research on college-level interventions (e.g. Angrist et al., 2009) has identified heterogeneous impacts of services for college achievement on different student subgroups; yet, the extent to which the effects of remediation may vary by institutional and individual characteristics has been largely ignored in current literature.

The current study presents new evidence on the effect of remediation using a large longitudinal data set of Virginia community college students and extends our understanding of the effectiveness of remediation by examining the causal impact of different levels of reading and writing remediation on academic outcomes and potential heterogeneous impact of remediation by subgroups of students and institutions. Taking advantage of the fact that during the time period of the study, the Virginia Community College System (VCCS) used standardized tests to place students into different levels of remediation, this study was able to use a regression discontinuity design to isolate the causal effects of multiple levels of remediation on three short-term outcomes: first-year dropout, enrollment in the first college-level English course (English "gatekeeper") and successful completion the English gatekeeper course, as well as three long-term outcomes: total number of credits earned in five years, total number of college-level credits earned in five years, and whether earning a degree or transfer to a four-year university in five years.

The results suggest that remedial courses do differ in their impact by the level of student preparation; yet, the analysis provides little indication that students benefit from remediation. While the estimated effects are generally small in magnitude and statistically insignificant for students on the margin of needing remediation, the impacts are negative and significant for lower-level remediation for most of the academic outcomes explored. In addition, subgroup analysis indicate that the negative impacts on students assigned to lower level remediation vary by institution, with stronger negative coefficients among colleges with higher proportion of students in remediation. This provides evidence to the hypothesis that assignment to remediation might worsen academic outcomes through "peer effects", where having more low-ability peers might induce greater negative effect on own outcomes. Finally, I find that the negative impacts also vary by types of students, with stronger negative impacts on females, younger students, and black students.

The current study extends the literature in several important ways. First, using a unique, large administrative dataset, this study explores the impacts of remediation in multiple community colleges in Virginia, whose research findings might be useful to policy makers, teachers, and students both in and out of the state. In addition, employing a regression discontinuity design, this study estimates the causal impacts of different levels of reading and writing remediation on a comprehensive set of both short term and long term academic outcomes. More importantly, it sets out as the first study to systematically explore potential variations in the impacts of remediation by institution and student characteristics. Virginia is in the process of redesigning its reading and writing developmental education system. The results of this study will thus assist the state in its planning by providing information about what should be changed to make remediation more effective.

The remainder of this paper is organized as follows: section 2 describes the sample; section 3 introduces the empirical strategies; section 4 presents the results based on regression discontinuity designs; and section 5 discusses the implications of the findings and presents policy recommendations.

2. Data

2.1 Remediation in VCCS

Virginia is one of the several states that administer a multi-tiered statewide placement system to assign students to different levels of math, reading, and writing remedial courses. In order to standardize and streamline the placement testing process system-wide, the VCCS mandated that all of Virginia's 23 community colleges implement and use COMPASS as the primary tool[52] to place students into multiple levels of reading, writing, and math courses with three possible options each: lower-level remedial courses, higher-level remedial courses, and college-level math or English courses. As a result, students put into the lower level of remediation need to complete a sequence of courses to proceed through the lower level remediation, higher level remediation before they can take the first college level course in that subject. There are three math tests that students can choose from (Pre-Algebra, Algebra, and College Algebra), which varies in both test content and assignment criteria. This is likely to violate the key assumption underlying the identification strategy used in this study[53]. In contrast, the reading and writing tests are system wide, sharing the same level of difficulty. Accordingly, this study focuses on the causal impact of reading and writing remediation.

The criteria of remediation assignment vary from college to college; yet, the VCCS provides a narrow range for each level of a given subject within which colleges could set their own cut scores. Colleges may exempt student from taking COMPASS if

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[52] In addition to COMPASS, some colleges till offer the paper-and-pencil, ASSET placement test when computerized testing is not applicable (e.g. student not skilled or uncomfortable on computers, students without access to computers); yet, most colleges reported minimal use of the ASSET test (Schmidt, Javanovich, & Dowing, 2007)

[53] The key assumption underlying the regression discontinuity design is that students around the cutoff score should be similar to each other. However, since students might choose different math tests based on their own mathematical skills and since both the content and grading criteria vary across tests, students on the margin of needing remediation might be systematically different.

the student demonstrates his or her readiness for college-level work[54]. Among students who are not waived from placement testing, remediation is mandated if students do not achieve minimal scores for a given level in a subject area. In a recent report on developmental education in VCCS (Schmidt, Javanovich, & Dowing, 2007), over 75% of colleges state that they use automated system indicators to enforce developmental education placement policies by blocking students' enrollments in certain college-level courses until completion of required developmental coursework.

Depending on the level of the remediation, courses are typically offered for credit, but rarely are they counted toward graduation requirements. Research suggests that students assigned to remedial courses are also likely to be assigned to remedial courses in other subjects (U.S. Department of Education, National Center for Education Statistics, 2004). The Report of The Developmental Education Task Force in Virginia (2009) indicates that among the 2004 first-time-in-college, program-placed students, over half (52%) enrolled in at least one developmental course; of those, 43% took more than one developmental course (Report of The Developmental Education Task Force, 2009). The fact that underprepared students often face multiple requirements of remediation in more than one subject implies substantial academic and economic burden on these students. Indeed, though varied across schools, developmental courses are generally suffering from a high dropout rate and low completion rate; of those beginning in developmental mathematics, only 36% enrolled in a gatekeeper, college-level math course within four years (Report of The Developmental Education Task Force, 2009). These high rates of failure in

[54] The exemptions that allow a student to be waived from placement testing include: SAT®, ACT®, or Advanced Placement (AP®) scores; academic performance in or completion of designated high school courses; previous remedial coursework; previous college-level English and/or mathematics; four-year college degree; enrollment in non-credit courses or credit courses with no English or mathematics.

developmental courses and low likelihood of moving on to a college-level course lead many into the wonder that assignment to remedial education might actually create barriers rather than assistance to students despite its initial intent. However, the descriptive results presented in these reports are confounded with differences in individual academic capacity between remedial students and college-ready students, thus disabling a conclusion regarding the causal impact of remediation.

2.2 Data Description

This study presents causal evidence on the effect of remediation using a large longitudinal dataset containing around 46, 000 students across 23 community colleges in Virginia who had valid information on college placement test scores on both reading and writing. First-time students who initially enrolled during the summer or fall of 2004, 2005, and 2006 were tracked until the spring semester of 2011, approximately 5 years for the 2006 cohort. The dataset contains information on student demographics, institutions attended, developmental placement scores for reading, writing, math, transcript data on courses taken and grades received, and information on educational attainment. The 23 Virginia 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. Overall, however, Virginia community colleges seem to represent a rural, low-income, underfunded and African-American student population[55].

[55] This description is based on statistics reported to the Integrated Postsecondary Education Data System (IPEDS) database. However, when comparing the characteristics of Virginia’s community colleges to U.S. community colleges as a whole, none of these institutional differences reach statistical significance at the 0.05 level.

Among all the 46, 632 students who took both reading and writing COMPASS tests, 72% were college ready in reading while less than 60% were college ready in writing. Table 3.1 presents assignment distribution in the full sample as well as across cohorts. Overall, 17% students were assigned to higher level reading versus 10% to lower level reading; 22% were assigned to higher level writing versus nearly 20% to lower level writing. The assignment distribution is fairly consistent across cohorts for both subjects, which is consistent with the report on developmental education in VCCS (Report of The Developmental Education Task Force, 2009) that the remediation policy remained constant from 2003 through 2006.

2.3 Outcome Measures

The outcome measures explored in the current study are divided into short- and long-term outcomes. One of the major criticisms leveled against remediation is that it imposes both economic and academic burden on students by requiring substantial amount of time spent on remediation that does not count toward a degree. Accordingly, of particular interest in current literature on college remediation is whether these requirements are so burdensome that students become discouraged and drop out of college in earlier stage of their college career. I examined this possibility by including first-year dropout as a short-term outcome measure. Given that the purpose of remediation is to prepare students for college-level course, I also explored whether receiving reading and writing remedial education would lead to higher probability of enrollment in the first college-level English course (ENG111), and among those who enrolled in ENG111, whether taking remediation helped them pass the course. Introductory college-level English and Math represent essential prerequisites for most degrees and certificates, and as such are commonly termed “gatekeeper” courses. Therefore, successful completion of gatekeeper courses plays a critical role in one’s college career; passing the initial college-level courses results in a substantially higher probability of earning a postsecondary credential (Calcagno, Crosta, Bailey, & Jenkins, 2007). As a result, community colleges tend to be particularly concerned with success rates in these courses and whether remediation actually leads to improved skills that are required for college-level courses down the road.

In terms of long-term outcomes, this study examined the impacts of remediation on the total number of credits attempted within 5 years, total number of college-level credits attempted in 5 years, and whether a student earn any degree or certificate or transfers up to a four-year school in 5 years. Most previous studies on remediation in four-year universities focused on the impact of remediation on degree attainment. However, in community colleges, transfer to a four-year university is the educational intention as well as a desirable educational outcome for a substantial number of students initially enrolled in community colleges (Rouse, 1995; Cohen & Brawer, 2003; Leigh & Gill, 2003; Ehrenberg & Smith, 2004). As a result, neglecting four-year university transfer reflects a misunderstanding of the diverse missions that community colleges assume. Some studies examining remediation in community colleges explored the impact of remediation on the probability of transfer to a four-year university in addition to the probability of degree attainment as two separate outcomes (e.g. Martorell & McFarlin, 2009). One potential problem with this approach, however, is that a substantial amount of community college students transfer to a four-year university prior to earning a credential (Calcagno et al., 2006). According to a recent study on degree completion in community colleges (Jenkins, 2011), about 15 percent of first-time students transferred to a four-year institution without having first earned any community college credential. Counting these students simply as “dropout” versus degree receiver would lead to biased estimate of the impact of remediation on degree attainment if remediation has a substantial impact on the likelihood of transferring to a four-year university. Given these concerns, this study combined degree attainment with transfer in five years as one measure and explored the impact of remediation on the probability of achieving it as a desirable academic outcome for a community college student.

3. Method

3.1 Addressing Ability Sorting: Regression Discontinuity Strategy

In order to draw a causal inference regarding the different levels of reading and writing remediation on educational outcomes, this study used a regression discontinuity design (RD). Specifically, I exploit the fact that during the time period of the study, the Virginia Community College System used standardized tests to place students into different levels of remediation. These mandatory cutoff scores created a discontinuity in the probability of receiving different levels of remedial treatment. The basic implementation of the RD design identifies the impact of remediation by comparing outcomes of students who score barely above the cutoff scores with those who score barely below; these students sharply differ in remediation assignment, yet are otherwise very similar. As a result, the regression coefficient can be then interpreted as the causal impact of the intervention for students on the margin of passing the cutoff (Levin & Calcagno, 2008).

While it is straightforward to estimate the linear regressions within a given window of bandwidth around a cutoff point, a critical question is the selection of the bandwidth within which the analysis should be conducted. Lee & Lemieux (2009) specified the tradeoff between precision and bias when finding an optimal bandwidth. On one hand, using a larger bandwidth yields more precise estimates; on the other hand, the linear specification is less likely to be accurate when a larger bandwidth is used, which can bias the estimate of the treatment effects. To identify the optimal bandwidth, I used the cross-validation procedure developed by Imbens & Lemieux (2009). The basic idea behind this procedure is to identify a bandwidth within which the functional form fits the data in an optimal way. Specifically, I estimated a linear regression to predict a given outcome variable within a set of different bandwidths. The bandwidth that minimizes the summation of the squared residuals then represents the best fit of the regression model to the data. The preferred bandwidth that I obtained using this particular procedure ranges depending on the cutoff explored and the outcome used, where most of them are around +/-5 points. Accordingly, I reported results using a +/- 5 points bandwidth but conducted sensitivity analysis using ½ of the bandwidths (+/- 2 points) and twice the bandwidths (+/-10).

There are two testable assumptions underlying the validity of the regression discontinuity design: (1) the probability of remedial enrollment should be discontinuous at the passing cut off, and (2) the expectations of pre-treatment covariates should be continuous at the passing cut off (Lee, 2008). Figure 1 and Figure 2 presents visual evidence on the validity of the two assumptions. Figure 1 plots the likelihood of being in remediation in a certain level of either reading or writing as a function of the corresponding college pretest scores (centered to be zero at the passing cutoff). The four graphs clearly show a discontinuity at each cut out score for both reading and writing.

To test the second assumption, I conducted t-tests to examine whether baseline characteristics exhibited discontinuities at each cutoff, a test for random assignment around the discontinuity point (Imbens & Lemieux, 2008; Lee, 2008). If there were systematic sorting at the cutoff, I should observe significant differences in individual characteristics between students on the two sides of the score. The results are presented in Table 3.2. Comparisons between students just above (within a 5 point bandwidth) or just below (within a 5 point bandwidth) the cutoff revealed no significant difference in terms of most pre-treatment characteristics for either reading or writing. There are a few instances where there are significant differences in race, dual enrollment and eligibility to financial aid; yet, none of these variables demonstrates consistent differences across all the cutoffs, indicating that these differences might be purely due to chance, which is often observed even in a randomized experiment. To make a contrast with the visual demonstration of discontinuities of remedial course enrollment against test scores shown in Figure 1, Figure 2 visually presents the distribution of pretest scores by gender as an example of student-level covariates around the four cutoffs (higher-level reading remediation; lower-level reading remediation; higher-level writing remediation; lower-level writing remediation) and none of them shows clear patterns of discontinuity at the cutoff. These results support the employment of the RD design in examining the causal impact of different levels of reading and writing remediation on educational outcomes.

Given the concern about statistical power, I conducted analysis on the full student sample across all the 23 community colleges instead of running regression on individual institution. Yet, I included college fixed effects into our model to account for nonrandom clustering of students within a college.

3.2 Addressing Noncompliance: Fuzzy RD Design

The traditional RD method, known as a “sharp RD,” assumes full compliance with recommendations based on the test cutoff. In Virginia, however, not all students followed the assignment during the time period under study (Jenkins, Jaggars, Roksa, Zeidenberg, & Cho, 2009). Accordingly, the average probability of enrollment in remedial courses is less than one below the cutoff and more than zero above the cutoff. To deal with potential bias associated with noncompliance, this study follows a “fuzzy RD” design, using remediation assignments as instrumental variables and employing a two-stage least squares strategy to provide an unbiased estimate of the remediation effects of reading and writing on academic outcomes.

I tested whether remediation assignment is a valid instrumental variable for actual enrollment. First stage instrumental variable analyses revealed significantly positive relationships between being recommended to and actually enrolling in a given level of remediation for each subject. This significant relationship remains even after controlling for all available students’ baseline characteristics. In addition, the correlations between recommendation status and enrollment are generally strong (0.60 for higher level reading, 0.76 for lower level reading, 0.74 for lower level writing, 0.46 for higher level writing), which rules out the problem of a weak instrument.

One important aspect of RD design, however, is that it provides estimates of the "local average treatment effects" (LATE; Imbens & Angrist, 1994) for a subpopulation around the cutoff points. Using an instrumental variable strategy, the fuzzy RD design further restricts the relevant subpopulation to that of compliers of the remediation assignment. Although estimates from an RD design have been criticized for its limited external validity, the local average effects estimated by the current study are informative about the students whom the remediation policy intends to address. The results are therefore clearly relevant to policymakers, particularly given VCCS's recent concerns about changing the location of the threshold.

4. Results

4.1 Impact of Higher-Level Remediation on Educational Outcomes

Table 3.3 reports results of the impact of higher-level reading (upper panel) and higher-level writing (bottom panel) on a variety of outcomes within a +/-5 points bandwidths. In each panel, the first row reports the average raw difference between individuals above the cutoff score and those below; the second row reports estimates using the fuzzy RD design, which includes controls for test score of the subject, a quadratic term of the test score, age, gender, race, whether the student is on a transfer-oriented or workforce track, eligibility for federal need-based financial aid, and dual enrollment status.

The results show negative and significant raw effects of higher-level remediation on educational outcomes for both reading and writing. Yet, these raw differences generally vanish after I included covariates and used IV strategy to address non-compliance, suggesting that there were systematic sorting around the cutoff score due to non-compliance. Higher-level remediation in both subjects has non-significant impacts on any of the six academic outcomes except for earning a degree or transfer to a four-year university in 5 years, where enrollment in higher level reading remediation reduces the probability of achieving this outcome by around 10 percentage points. However, this negative impact is barely significant at the 0.05 level, and the corresponding estimate is not significant even at the 0.1 level for high-level writing. Accordingly, our results generally support the current literature (e.g. Calcagno & Long, 2008; Martorell & McFarlin, 2009) that remediation has little impact on academic outcomes for students on the margin of needing remediation.

4.2 Impact of Lower-Level Remediation on Educational Outcomes

Table 3.4 reports results of the impact of lower-level reading (upper panel) and lower-level writing (bottom panel) on educational outcomes, using the same model presented in Table 3.3. In contrast to the general non-significant patterns across estimates, lower-level remediation shows substantial and significant negative impacts on the academic outcomes, particularly for reading remediation, where all the estimates are significant except for passing the English gatekeeper course.

Lower-level remediation in both subjects shows a significant negative impact on first-year dropout rate, where taking reading remediation increases the probability of dropping out of college within the first year by 13 percentage points ($p < 0.1$) whereas taking writing remediation increase the probability even greater (18 percentage points, $p < 0.1$). This finding supports the concern that assignment to remedial courses might slow students down in their early progress toward degree so much that students become discouraged and choose to drop out of college. As mentioned earlier in section 2.1, students put into the lower level of remediation need to complete a sequence of courses to proceed through the lower level remediation, higher level remediation before they can take the first college level English course in that subject. Since these course are typically not counted toward a degree, being assigned to a lower level remediation implies much greater burden on students both academically and economically compared to those assigned to higher level remediation, which also explains why I observed non-significant impact of taking higher level remediation on first year dropout but significant and substantially negative impact of taking lower level reading and writing on this short-term outcome. Associated with this negative impact of remediation on retention is a reduced probability of ever attempting the English gatekeeper course. As shown in Table 3.3, barely-passers of lower-level reading remediation were more likely to enroll in the English gatekeeper course by 16 percentage points, which is significant at the 0.05 level. I then examined whether taking remediation can improve the probability of passing the English gatekeeper course among those who enrolled in ENG111. Given that the purpose of reading and writing remediation is to improve skills that are required for college-level English course, the impact of remediation on this particular outcome is of great policy interest. However, our results provide no evidence that taking remediation actually increase the probability of passing an English gatekeeper course. The estimates are consistently small and insignificant for either higher-level remediation or lower-level remediation for both subjects.

The little assistance of lower-level remediation on passing the English gatekeeper, together with its significant negative impacts on early dropout caused us to wonder whether assignment to lower-level remediation may lead to larger disparities in student performance over time. Indeed, as shown in Table 3.3, being in reading remediation reduces both total credits and college-level credits in five years by about 10 points, both of which are significant at the 0.05 level. Taking remediation also reduces the likelihood of earning a degree or transferring up to a four-year university in five years by 14 percentage points ($p<0.05$). As for writing remediation, the estimates for all the three outcomes were also negative, though only the impact on the total college-level credits is significant ($p<0.1$). However, one concern is that the negative impacts of lower-level remediation on long-term outcomes are mainly due to its negative impact on early college dropout. I explored this possibility by estimating the long-term impact on a reduced sample where students retained into the second year. Yet, the results were qualitatively similar to those presented in Table 3.3, suggesting that assignment to lower-level remediation continues as a barrier to academic progress even beyond early stage of the college career. The negative impacts on degree completion and transfer are particularly alarming, given that research has generally shown that completion of a certificate, an associate degree, or transfer to a higher-level college has positive effects on earnings (Jaeger & Page, 1996; Kane & Rouse, 1999).

4.3 Heterogeneous Impacts of Remediation

To examine whether the aggregate estimates mask benefits for certain groups of students, I examined the effect of remediation by subgroup. First, I examined the results by the proportion of remedial students at a given college. I computed the distribution of the fraction of students in remediation and split the sample into whether a student was in a school in the top quarter or bottom quarter of this distribution. The results are consistent across subject and level of remediation explored; I presented detailed results from lower-level reading remediation as an illustration in in Table 3.5. As shown in the top panel, remediation has sizable and significant negative effects on academic outcomes in high-remediation institutions and smaller and non-significant effects in low-remediation school. The same pattern was also observed in other studies exploring heterogeneous impacts of remediation (e.g. Martorell & McFarlin, 2009) on academic outcomes and one possible explanation for this divergence, as indicated by Martorell & McFarlin (2009), is that the quality of remedial programs is diluted by the relatively high number of students in remediation. Another possibility is that assignment to remediation might worsen academic outcomes through "peer effects", where having more low-ability peers might induce greater negative effect on own outcomes.

In addition to subgroup analysis by institution, I also explored possible heterogeneous impacts by the type of students. I found that the negative impact of remediation were generally non-significant among males, older students and white students whereas the impact were substantial and significant for females younger students and black students. A possible explanation for such variation is that students along different demographic lines might react in different ways toward the unintended negative impact of remediation academically, economically, and psychologically. For example, the peer effects and economic burden might be less strong for older students (students who entered college after 25) who are more likely to be economically independent and influenced by peer groups compared to younger students. These findings lend support to the argument (e.g. Angrist et al., 2009) that college-level interventions typically vary substantially among demographic lines and neglecting the heterogeneity of remediation among different types of students can overlook important policy implications.

5. Conclusion

The effects of remediation on helping underprepared students succeed in college are of great interest to policy makers, school administrators, and taxpayers. Using a regression discontinuity design, this study extends current understanding of college remediation by exploring the impact of different levels of remedial assignment on students' short-term and long-term academic outcomes in an entire community college system. The current results suggest that remedial courses do differ in their impact by the level of student preparation. Specifically, while the estimated effects are generally small in magnitude and statistically insignificant for students on the margin of needing remediation, the impacts are negative and significant for lower-level remediation for most of the academic outcomes explored. In addition, this negative impact is even larger in institution with higher proportion of students in remediation, implying that assignment to remediation might worsen academic outcomes through “peer effects”, where having more low-ability peers might induce greater negative effect on own outcomes.

These results have several important policy implications. First, they suggest that the traditional drill-and-skill approach, as largely used in the remedial courses at community colleges, are not productive in assisting academic progress. Accordingly, community colleges may need to carry out formal evaluations of different remedial approaches to test their efficacy and cost-effectiveness in for der to pursue a wise remediation strategy. Second, the consistent negative impacts observed on lower-level reading and writing remediation on student outcomes provides evidence to the concern that remediation may bring about unintended effects through the psychological, academic, and economic burdens it imposes on students assigned to lower level of remediation. Accordingly, community colleges might need to consider changing the current remediation mechanism, either to speed up the remedial process, or to provide additional financial and academic support to students facing multiple remedial course requirements.

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TABLES

Table 1.1.1. Characteristics of Washington State Community and Technical Colleges vs. All U.S. Public Two-Year Colleges

Variables	All U.S. Public Two-Year Colleges	Washington State Two-Year Colleges
Student Demographics		
% White	65.89 (23.69)	67.06 (12.96)
% Black	14.22 (17.02)	3.82 (3.11)
% Hispanic	8.54 (13.67)	5.68 (5.67)
% Receive Federal Financial Aid	43.94 (18.71)	27.94 (10.63)
% Enrolled Full-Time	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)
Expenditures (Dollars per FTE)		
Instructional	5261.52 (20987.74)	4848.71 (2133.11)
Academic	1003.05 (4365.67)	578.26 (229.78)
Institutional	1684.28 (4236.92)	1302.03 (1391.40)
Student	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.
Source of data: Statistics reported to the 2004 Integrated Postsecondary Education Data System (IPEDS) database.

Table 1.1.2. Summary Statistics

I. Student-Level Characteristics	Full Student Sample	Ever Online Student Sample	Never Online Student Sample	Diff (Ever - Never)
Demographic Characteristics				
Female	0.525 (0.499) †	0.571 (0.495)	0.475 (0.499)	0.096***
White	0.697 (0.460)	0.710 (0.454)	0.682 (0.466)	0.028***
African American	0.044 (0.205)	0.037 (0.188)	0.052 (0.222)	-0.015***
Hispanic	0.022 (0.148)	0.021 (0.143)	0.024 (0.154)	-0.003
American Indian	0.014 (0.118)	0.012 (0.108)	0.017 (0.129)	-0.005***
Asian	0.075 (0.264)	0.077 (0.266)	0.074 (0.262)	0.003
Alaska Native	0.001 (0.034)	0.001 (0.029)	0.001 (0.038)	0.000
Native Hawaiian	0.004 (0.060)	0.004 (0.059)	0.004 (0.062)	0.000
Pacific Islander	0.002 (0.050)	0.001 (0.035)	0.004 (0.062)	-0.003***
Multiracial	0.041 (0.199)	0.042 (0.200)	0.041 (0.198)	0.001
Unknown Race	0.062 (0.242)	0.061 (0.239)	0.064 (0.245)	-0.003
Age	21.304 (6.585)	21.444 (6.641)	21.151 (6.521)	0.293***
Eligible for Need-Based Aid	0.421 (0.494)	0.444 (0.497)	0.397 (0.489)	0.047***
Highest SES	0.177 (0.382)	0.188 (0.391)	0.165 (0.371)	0.023***
Higher SES	0.223 (0.417)	0.229 (0.420)	0.218 (0.413)	0.011*
Middle SES	0.206 (0.405)	0.202 (0.402)	0.211 (0.408)	-0.009
Lower SES	0.180 (0.385)	0.176 (0.381)	0.185 (0.388)	-0.009
Lowest SES	0.137 (0.344)	0.131 (0.337)	0.145 (0.351)	-0.014***
Unknown SES	0.076 (0.265)	0.074 (0.263)	0.078 (0.267)	-0.004
Hours Worked Per Week	14.889 (13.38)	15.536 (13.20)	14.187(13.36)	1.349***
Distance to College in Miles	17.248(13.895)	17.537(14.228)	16.935(13.51)	0.602***
Academic Characteristics				
Took Developmental Ed.	0.601 (0.490)	0.594 (0.491)	0.607 (0.489)	-0.013*
Limited English Proficiency	0.002 (0.040)	0.002 (0.041)	0.002 (0.040)	0.000
Dual Enrolled Prior to Entry	0.087 (0.282)	0.094 (0.292)	0.080 (0.272)	0.014***
GPA in First Term††	2.888 (0.947)	2.981 (0.872)	2.784 (1.014)	0.197***
Credits Accrued First Term	11.200 (4.857)	11.633 (4.717)	10.731(4.963)	0.902***
Credits Taken Per Term	12.847 (3.302)	13.032 (3.109)	12.650 (3.484)	0.383***
Observations	18,567	9,655	8,912	

II. Course-Level Characteristics and Outcomes	Full Course Sample	Online Course Sample	Face-to-Face Course Sample	Difference
Online Delivery Format	0.218 (0.413)	1.000 (0.000)	0.000 (0.000)	-
Course Persistence	0.933 (0.249)	0.907 (0.293)	0.941 (0.235)	-0.034***
Course Grade†††	2.652 (1.281)	2.539 (1.416)	2.682 (1.240)	-0.143***
Observations	125,218	27,331	97,887	

*Significant at the 10% level **Significant at the 5% level***Significant at the 1% level
† Standard deviations are in parentheses.

†† For "GPA at the end of first term" N = 17,355 for the full course sample, N = 9,170 for the ever online student sample, and N = 8,185 for the never online student sample.
††† For "Course Grade" N = 116,830 for the full course sample.

Table 1.1.3. OLS/Probit Estimates of the Impact of the Online Format (and Each Covariate) on Course Persistence and Course Grade

	Course Persistence		Course Grade	
	Coefficient (se)		Coefficient (se)	
Online Delivery Format	-0.257***	(0.018)	-0.197***	(0.018)
(Marginal Effect)	-0.036***	(0.003)	-	
Covariates: Demographic Characteristics				
Female	0.007***	(0.002)	0.198***	(0.009)
African American (Base Group: White)	-0.014***	(0.005)	-0.464***	(0.024)
Hispanic	-0.017***	(0.007)	-0.169***	(0.038)
American Indian	-0.020***	(0.008)	-0.257***	(0.040)
Asian	-0.006**	(0.003)	-0.021	(0.018)
Alaska Native	-0.097***	(0.039)	-0.627***	(0.141)
Native Hawaiian	-0.032**	(0.016)	-0.168***	(0.063)
Pacific Islander	-0.036**	(0.021)	-0.544***	(0.097)
Multi-Racial	-0.014***	(0.004)	-0.225***	(0.023)
Unknown Race	0.002	(0.003)	0.041**	(0.019)
Age	0.000	(0.000)	0.024***	(0.001)
Eligible for Need-based Aid	0.017***	(0.002)	0.081***	(0.010)
Higher SES (Base Group: Highest SES)	-0.003	(0.002)	-0.041***	(0.014)
Middle SES	-0.010***	(0.003)	0.002	(0.016)
Lower SES	-0.001	(0.003)	-0.013	(0.017)
Lowest SES	-0.014***	(0.003)	-0.121***	(0.019)
Unknown SES	0.005	(0.004)	0.045**	(0.021)
Hours Worked Per Week	-0.000***	(0.000)	-0.002***	(0.000)
Covariates: Academic Characteristics				
Took Developmental Education	-0.003	(0.002)	-0.141***	(0.011)
Limited English Proficiency	0.026	(0.013)	0.198**	(0.083)
Dual Enrolled Prior to Entry	-0.002	(0.003)	0.127***	(0.016)
Credits Taken This Term	-0.001***	(0.000)	0.019***	(0.003)
Enrolled Full Time This Term	0.012***	(0.003)	-0.048**	(0.019)
Observations	125,218		116,830	

*** Significant at the 1% level **Significant at the 5% level

Notes: Because the data include multiple observations within each course, standard errors for all models are adjusted for clustering at the course level.[56] We used the student-level variable "average credits taken per term" in Table 1.1. 1 to describe student sample characteristics; in the regression analysis on the course-level sample, we used the course-level variable of the actual number of credits enrolled in the given term as the covariate.

[56] Please see Wooldridge (2003) for a detailed discussion of the necessity and methods of adjusting standard errors when individual observations are clustered.

Table 1.1.4. Estimates of the Effect of Taking a Course Online, Based on Different Model Specifications

	OLS/Probit Estimates			IV Estimates		
	Baseline	Adding Time, College & Subject FE	Adding Course FE	Baseline	Adding time, College & Subject FE	Adding Course FE
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Course Persistence						
Online Format	-0.257***	-0.298***	-0.311***	-0.425**	-0.515**	-0.579**
(SE)	(0.018)-	(0.017)	(0.017)	(0.198)	(0.215)	(0.028)
Marginal Effect	0.036***	-0.041)**	-0.044**	-0.055**	-0.066**	-0.072**
(SE)	(0.003)	(0.003)	(0.003)	(0.027)	(0.030)	(0.033)
Dependent Variable: Course Grade						
Online Format	-0.196***	-0.233***	-0.266***	-0.299**	-0.347**	-0.430**
(SE)	(0.018)	(0.017)	(0.016)	(0.150)	(0.160)	(0.184)
College & Subject FE	No	Yes	Yes	No	Yes	Yes
Year-Term FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	No	Yes	No	No	Yes

*** Significant at the 1% level **Significant at the 5% level

Notes: N = 125, 218 for the analysis on course persistence; N = 116, 820 for the analysis on course grade. Standard errors for all models are adjusted for clustering at the course level. Each cell represents a different regression specification. All models also include the following covariates: gender, ethnicity dummy variables, socioeconomic status dummy variables, receipt of federal financial aid, limited English proficiency, dual enrolled prior to college, ever enrolled in remedial courses, total credits taken in that term, total working hours in that term, and full-time (vs. part-time) college enrollment in that term.

Table 1.1.5. Results of Probit Model for First-Stage IV (Probability of Taking a Course Online)

	Baseline (1)	Adding time, College & Subject FE (2)	Adding Course FE (3)
Distance to College	0.007***	0.007***	0.007***
(SE)	(0.0005)	(0.0004)	(0.0004)
Marginal Effect	0.002***	0.002***	0.002***
(SE)	(0.0003)	(0.0002)	(0.0001)
College & Subject FE	No	Yes	Yes
Year-Term FE	No	Yes	Yes
Course FE	No	No	No
F-test on Excluded Instruments	174.13	180.20	163.03
(Prob > F)	<0.001	<0.001	<0.001

*** Significant at the 1% level

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

Table 1.1.6. Estimates of the Effect of Distance (in Miles) on Face-to-Face Course Outcomes

	Baseline (1)	Adding Time, College & Subject FE (2)	Adding Course FE (3)
Dependent Variable: Course Persistence			
Distance in Miles	0.0002	0.0002	0.0002
(SE)	(0.0006)	(0.0006)	(0.0006)
Marginal Effect	0.00003	0.00002	0.00002
(SE)	(0.00007)	(0.00006)	(0.00006)
Dependent Variable: Course Grade			
Distance	-0.0003	-0.0004	-0.0004
(SE)	(0.0003)	(0.0003)	(0.0003)
College & Subject FE	No	Yes	Yes
Year-Term FE	No	Yes	Yes
Course FE	No	No	Yes

Notes: All estimates failed to reach statistical significance at the $p < 0.10$ level. N = 97,887 for the analysis on course persistence; N = 92,140 for the analysis on course grade. Standard errors for all models are adjusted for clustering at the course level. Each cell represents a different regression specification. All models also include the following covariates: gender, ethnicity dummy variables, socioeconomic status dummy variables, receipt of federal financial aid, limited English proficiency, dual enrolled prior to college, ever enrolled in remedial courses, total credits taken in that term, total working hours in that term, and full-time (vs. part-time) college enrollment in that term.

Table 1.2.1 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 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 (in dollars)		
Instructional expenditures per FTE	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

Notes: Standard deviations for continuous variables are in parentheses.

Table 1.2.2 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**

Table 1.2.3 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.

Table 1.2.4 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.

Table 1.2.5 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 1.2.2.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 2.1 Summary Statistics of the Student-Level and Course-Level Data of the 2007-2008 cohort at the Large Community College System (LCCS)

I. Student-Level Characteristics			
	LCCS Student Sample		
Females	0.55		
White Students	0.63		
Black students	0.22		
Hispanic Students	0.07		
Asian Students	0.06		
Other/Unknown Race	0.02		
Age at College Entry	21.52 (6.65)		
Transfer-Oriented (vs. Tech-Oriented)	0.60		
Dual-Enrolled prior to College Entry	0.15		
Eligible to Need-based Financial Aid	0.41		
Took English or Math Remediation	0.55		
Observations	26,030		
II. Student-Course Level Characteristics			
	Full Intro Course Sample	Courses by Adjuncts	Courses by Ft Faculty
Class Taught by Adjunct Instructor	0.49	-	-
Online Delivery Format	0.15	0.14**	0.17**
Credits Taken in the Current Semester	11.92 (3.71)	11.62 (3.79)**	12.20 (3.61)**
Class Size	14.71 (8.67)	13.02 (6.93) **	16.31 (9.78) **
Observations	144,024	69,926	74,098
III. ***Student-Course Level Outcomes***			
Contemporaneous outcomes	Full Intro Course Sample	Courses by Adjuncts	Courses by Ft Faculty
Received C or above in the Current Course	0.68	0.70**	0.66**
Persisted to the End of the Course	0.89	0.90**	0.89**
Course Grade (0 to 4 Grading Scale)	2.47 (1.39)[a]	2.57 (1.38)**	2.38 (1.39)**
Observations	144,024	69,926	74,098
Subsequent outcomes			
Took Additional Course in the Same Field	0.43	0.41**	0.45**
Total Subsequent Credits in the Same Field	2.83 (5.63)	2.55 (5.12)**	3.08 (6.05)**
Received C or above in the Subsequent Course in the Same Field	0.73 [b]	0.73	0.73
Observations	137,522	66,224	71,298

Notes: [a] N=128,331 for course grade. [b] N = 59,502 for subsequent course completion
Standard deviations of the continuous variables are shown in the parentheses.
** indicates that the t-statistic is significant at the 5% level between courses taught by adjuncts and courses taught by full-time faculty.
The student-course sample is restricted to the first college-level course taken in a subject that offered sections taught by both full-time faculty and adjuncts within a college.

Table 2.2 Proportion of Enrollments with an Adjunct Instructor by Subject

Subject Area	Introductory Courses		Full Course Sample	
	Percent by Adjuncts	Total Enrollments	Percent by Adjuncts	Total Enrollments
Health	**58.81%**	**6,642**	**51.64%**	**14,594**
Foreign Language	**56.44%**	**3,455**	**52.16%**	**5,753**
Humanities	**54.87%**	**42,590**	**54.04%**	**85,207**
English	53.34%	22,260	52.24%	51,471
Philosophy	67.71%	3,038	70.19%	3,690
Religion	70.97%	1,409	71.54%	1,634
History	52.68%	13,992	54.08%	26,077
Other	56.43%	1,891	55.33%	2,335
Fine Arts	**53.41%**	**4,746**	**53.89%**	**8,757**
Natural Science	**48.09%**	**15,468**	**46.47%**	**27,536**
Biology	50.22%	10,591	48.05%	19,017
Physics	43.47%	4,877	42.93%	8,519
Public Service	**46.42%**	**3,352**	**49.43%**	**9,049**
Social Sciences	**44.69%**	**27,313**	**45.77%**	**39,513**
Economics	41.52%	5,188	40.53%	7,253
Geography	60.85%	562	64.51%	665
Political Science	59.51%	1,383	65.67%	2,575
Sociology	41.32%	7,429	42.42%	8,994
Psychology	43.53%	12,644	45.82%	19,919
Other	79.44%	107	79.44%	107
Computer Science	**44.59%**	**14,773**	**44.40%**	**21,017**
Business	**41.62%**	**9,002**	**43.35%**	**22,066**
Math	**40.03%**	**12,283**	**39.75%**	**24,430**
Technology	**38.95%**	**4,400**	**40.03%**	**12,012**
Mechanical Technology	33.09%	2,835	38.08%	9,586
Science Technology	49.58%	1,565	47.73%	**2,426**
Total	**48.55%**	**144,024**	**48.28%**	**269,934**

Table 2.3 Estimates of the Impacts of Adjuncts on a Student's First Course in a Subject Area

	OLS Estimates			IV Estimates		
	Baseline	Adding Time, College & Subject FE	Adding Course FE	Baseline	Adding time, College & Subject FE	Adding Course FE
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Completed the Course with C or above						
Adjunct Instructors	0.044***	0.048***	0.045***	0.041***	0.051***	0.038***
	(0.006)	(0.005)	(0.005)	(0.011)	(0.009)	(0.009)
R-squared	0.039	0.066	0.054	0.039	0.066	0.054
Observations	144,024	144,024	144,024	144,024	144,024	144,024
Dependent Variable: Persisted to the End of the Course						
Adjunct Instructors	0.012***	0.014***	0.013	0.008	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.006)	(0.005)	(0.005)
R-squared	0.012	0.024	0.015	0.012	0.024	0.015
Observations	144,024	144,024	144,024	144,024	144,024	144,024
Dependent Variable: Course Grade						
Adjunct Instructors	0.177***	0.190***	0.183***	0.171***	0.190***	0.144***
	(0.020)	(0.018)	(0.019)	(0.039)	(0.034)	(0.029)
R-squared	0.073	0.107	0.088	0.073	0.107	0.088
Observations	128,331	128,331	128,331	128,331	128,331	128,331
Initial Major FE	Yes	Yes	Yes	Yes	Yes	Yes
College & Subject FE	No	Yes	Yes	No	Yes	Yes
Semester FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	No	Yes	No	No	Yes

***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level

Table 2.4 Probability of Taking the First Course in a Subject Area with an Adjunct

	Baseline	Subject Fixed Effects	Adding Course Fixed Effects
Demographic Characteristics			
Age	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.001)
Age Squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Female	0.010**	0.001	-0.000
	(0.004)	(0.003)	(0.003)
Black	0.016**	0.005	-0.005
(Base Group: White)	(0.007)	(0.005)	(0.004)
American Indian	-0.021	-0.025	-0.028*
	(0.017)	(0.017)	(0.015)
Asian	-0.007	-0.003	-0.003
	(0.010)	(0.007)	(0.007)
Hispanic	0.004	0.006	0.002
	(0.010)	(0.006)	(0.006)
Unknown Race	0.003	0.006	0.004
	(0.009)	(0.006)	(0.006)
Receiving Financial Aid	-0.020***	-0.007**	-0.010***
	(0.005)	(0.003)	(0.003)
Academic Attributes			
Transfer-Oriented	0.020**	0.001	0.004
	(0.008)	(0.007)	(0.005)
Ever Dual Enrolled	-0.069***	-0.013**	-0.003
	(0.012)	(0.006)	(0.006)
Took Any Remedial Course	0.024***	0.005	0.001
	(0.005)	(0.003)	(0.003)
Semester-level Covariates			
Total Credits Attempted in the Current Semester	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
Course Section-level Covariates			
Total Section Enrollments	-0.011***	-0.012***	-0.015***
	(0.001)	(0.001)	(0.001)
Distance Course Section	-0.104***	-0.119***	-0.145***
	(0.016)	(0.015)	(0.015)
Initial Major FE	Yes	Yes	Yes
College & Subject FE	No	Yes	Yes
Year-Term FE	No	Yes	Yes
Course FE	No	No	Yes
R-Squared	0.055	0.106	0.069
Observations	144,024	144,024	144,024

Notes: ***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level
Standard errors are clustered at the college-course level due to multiple observations per course in a college.

Table 2.5 Results of First Stage IV Regressions (Probability of Taking the First Course in a Subject Area with an Adjunct)

	Baseline	Adding time, College & Subject FE	Adding Course FE
	(1)	(2)	(3)
Proportion of Sections Taught by Adjuncts	0.991*** (0.008)	0.980*** (0.009)	0.990*** (0.009)
Initial Major FE	Yes	Yes	Yes
College & Subject FE	No	Yes	Yes
Semester FE	No	Yes	Yes
Course FE	No	No	Yes
R-squared	0.298	0.307	0.190
Observations	144,024	144,024	144,024
F-test on Excluded Instruments	14345.32	12,668.71	12039.48
(Prob > F)	<0.001	<0.001	<0.001

Notes: ***Significant at the 1% level
Standard errors are clustered at the college-course level due to multiple observations per course in a college.

Table 2.6 Estimates of the Impacts of Adjuncts on Subsequent Interest and Course Performance

	OLS Estimates			IV Estimates		
	Baseline	Adding Time, College & Subject FE	Adding Course FE	Baseline	Adding time, College & Subject FE	Adding Course FE
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: Any Additional Course in the Same Subject Area						
Adjunct Instructors	-0.027***	-0.020***	-0.009***	-0.032	-0.036	-0.009
	(0.010)	(0.004)	(0.003)	(0.032)	(0.024)	(0.010)
R-squared	0.033	0.173	0.043	0.033	0.173	0.043
Observations	137,522	137,522	137,522	137,522	137,522	137,522
Dependent Variable: Total Subsequent Credits in the Same Subject Area						
Adjunct Instructors	-0.500***	-0.316***	-0.153***	-0.951***	-0.713***	-0.316**
	(0.079)	0.052)	0.035)	(0.251)	(0.171)	(0.132)
R-squared	0.020	0.136	0.027	0.019	0.134	0.027
Observations	137,522	137,522	137,522	137,522	137,522	137,522
Dependent Variable: Completed the Subsequent Course with C or above						
Adjunct Instructors	-0.008	-0.012***	-0.014***	-0.010	-0.011	-0.026**
	(0.005)	0.005)	(0.005)	(0.012)	(0.010)	(0.013)
R-squared	0.029	0.042	0.028	0.028	0.042	0.028
Observations	59,502	59,502	59,502	59,502	59,502	59,502
Dependent Variable: Persisted to the End of the Subsequent Course in the Same Subject Area						
Adjunct Instructors	-0.006**	-0.005**	-0.007**	-0.003	-0.003	-0.007
	(0.003)	(0.002)	(0.003)	(0.007)	(0.006)	(0.008)
R-squared	0.010	0.018	0.010	0.010	0.018	0.010
Observations	59,502	59,502	59,502	59,502	59,502	59,502
Dependent Variable: Course Grade in the Same Subject Area						
Adjunct Instructors	-0.013	-0.033**	-0.043***	-0.088**	-0.092***	-0.096**
	(0.016)	(0.014)	(0.014)	(0.043)	(0.033)	(0.042)
R-squared	0.061	0.079	0.061	0.059	0.079	0.061
Observations	54,178	54,178	54,178	54,178	54,178	54,178
Initial Major FE	Yes	Yes	Yes	Yes	Yes	Yes
College & Subject FE	No	Yes	Yes	No	Yes	Yes
Semester FE	No	Yes	Yes	No	Yes	Yes
Course FE	No	No	Yes	No	No	Yes

Table 2.7 OLS Estimates of the Impact of the Instrument on Courses with Full-time Instructors Only

	Baseline (1)	Adding Time, College & Subject FE (2)	Adding Course FE (3)
Dependent Variable: Completed the Current Course with C or above			
Proportion of Sections Taught by Adjuncts	-0.005 (0.017)	0.005 (0.016)	0.009 (0.017)
R-squared	0.040	0.070	0.056
Observations	74,098	74,098	74,098
Dependent Variable: Any Additional Course in the Same Subject Area			
Proportion of Sections Taught by Adjuncts	0.078* (0.040)	-0.014 (0.019)	0.024 (0.018)
R-squared	0.039	0.179	0.044
Observations	68,031	68,031	68,031
Dependent Variable: Total Subsequent Credits in the Subject Area			
Proportion of Sections Taught by Adjuncts	-0.957*** (0.343)	-0.275 (0.254)	-0.006 (0.243)
R-squared	0.027	0.144	0.029
Observations	68,031	68,031	68,031
Dependent Variable: Completed the Subsequent Course in the Same Subject Area with C or above			
Proportion of Sections Taught by Adjuncts	0.035** (0.015)	0.003 (0.015)	-0.004 (0.025)
R-squared	0.032	0.048	0.031
Observations	27,717	27,717	27,717
Initial Major FE	Yes	Yes	Yes
College & Subject FE	No	Yes	Yes
Semester FE	No	Yes	Yes
Course FE	No	No	Yes

Notes: ***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level
Standard errors are clustered at the college-course level due to multiple observations per course in a college.

Table 2.8 IV Estimates of the Impacts of Adjuncts on Course Outcomes by Subject Areas

	Current Outcomes			Subsequent Outcomes		
	Course Completion	Course Persistence	Course Grades	Additional Course in Subj	Total Additional Credits in Subj	Course Completion
Academic Subjects	0.033*** (0.011)	-0.002 (0.007)	0.137*** (0.037)	-0.0174 (0.012)	-0.073 (0.078)	-0.023 (0.015)
Natural Science	0.036 (0.023)	-0.020 (0.019)	0.151** (0.066)	-0.044 (0.031)	-0.118 (0.214)	-0.048 (0.036)
Humanities	0.023 (0.019)	0.002 (0.011)	0.028 (0.062)	-0.006 (0.022)	0.036 (0.142)	-0.015 (0.032)
Math	0.061** (0.031)	0.007 (0.021)	0.233** (0.097)	-0.019 (0.025)	-0.155 (0.201)	0.014 (0.036)
Social Sciences	0.037 (0.019)	0.002 (0.012)	0.206*** (0.067)	-0.017 (0.014)	-0.161** (0.075)	-0.027 (0.035)
Professional Subjects	0.044*** (0.014)	0.013* (0.008)	0.151*** (0.047)	0.00443 (0.016)	-0.758** (0.320)	-0.034** (0.017)
Business	0.058* (0.034)	0.011 (0.017)	0.172 (0.111)	-0.036 (0.033)	-0.786* (0.462)	-0.062* (0.037)
Computer Science	-0.043 (0.037)	-0.032 (0.023)	-0.129 (0.124)	-0.039 (0.034)	-0.965** (0.465)	-0.159** (0.074)
Health	0.045 (0.028)	-0.007 (0.017)	0.223** (0.108)	-0.031 (0.035)	-2.417*** (0.909)	-0.018 (0.042)
Technology	0.030 (0.033)	0.057*** (0.021)	-0.024 (0.102)	0.052 (0.035)	-0.561 (0.862)	-0.076** (0.038)
Public Service (e.g. Education)	0.075** (0.033)	0.041* (0.025)	0.208* (0.114)	0.119*** (0.039)	1.599* (0.857)	0.122** (0.053)
Applied Arts	0.045 (0.037)	0.023 (0.024)	0.204* (0.118)	0.026 (0.049)	-0.275 (0.694)	-0.207** (0.086)
Foreign Language	0.167*** (0.062)	0.020 (0.038)	0.613*** (0.176)	0.058 (0.062)	0.386 (0.371)	0.064 (0.088)

Notes: ***Significant at the 1% level **Significant at the 5% level *Significant at the 10% level
Notes: Each cell represents a separate regression using IV model with course and time fixed effects. Standard errors are clustered at the college-course level due to multiple observations per course in a college.

Table 3.1 Course Assignment for Students Taking COMPASS Reading and Writing

	Assignment to Reading Remediation			Assignment to Reading Remediation		
	College Reading	Higher Level Remediation	Lower Level Remediation	College Writing	Higher Level Remediation	Lower Level Remediation
Full Sample (N= 46, 632)						
	72.22%	17.74%	10.04%	59.75%	21.96%	18.29%
2004 Cohort (N= 14, 980)						
	71.76%	17.73%	10.51%	58.35%	22.76%	18.89%
2005 Cohort (N= 15, 221)						
	71.91%	17.66%	10.43%	57.10%	24.17%	18.73%
2006 Cohort (N= 16,431)						
	71.95%	18.82%	9.23%	61.73	21.47%	16.80%

Table 3.2 Descriptive Statistics of the Sample around Cutoffs: Group Means and Group Differences

	READING						WRITING					
	Band around College-Ready Cutoff: +/-5 points			Band around Higher-level Remediation Cutoff: +/-5 points			Band around College-Ready Cutoff: +/-5 points			Band around Higher-level Remediation Cutoff: +/-5 points		
	Below	Above	Diff	Below	Above	Diff	Below	Above	Diff	Below	Above	Diff
Demographic Characteristics												
Age at college entry	20.976	20.847	0.130	21.156	21.055	0.101	20.830	20.586	0.244	21.371	21.616	0.245
Female	0.599	0.587	0.012	0.615	0.622	0.007	0.542	0.527	0.015	0.542	0.542	<0.001
White	0.536	0.577	0.041**	0.440	0.463	0.023	0.612	0.634	0.022	0.506	0.507	0.001
Black	0.323	0.279	0.044**	0.420	0.391	0.029	0.219	0.204	0.015	0.319	0.359	0.040
American Indian	0.007	0.005	0.002	0.003	0.005	0.002	0.005	0.004	0.001	0.006	0.004	0.002
Asian	0.061	0.065	0.004	0.077	0.066	0.011	0.069	0.080	0.011	0.086	0.053	0.032**
Hispanic	0.073	0.075	0.002	0.073	0.062	0.011	0.082	0.086	0.004	0.082	0.077	0.005
Academic characteristics												
Dual enrolled prior to entry	0.059	0.067	0.008	0.037	0.054	0.017 **	0.059	0.047	0.011	0.042	0.038	0.004
Transfer track (vs. career-technical)	0.569	0.585	0.016	0.536	0.558	0.023	0.591	0.590	0.001	0.553	0.584	0.031
Federal financial aid recipient	0.381	0.369	0.013	0.460	0.439	0.021	0.322	0.298	0.024	0.418	0.471	0.053**
Observations	3,661	5,378	9,039	1,215	1,907	3,122	2,219	2,927	5,146	842	1,185	2,027

Table 3.3 Impact of Higher Level Reading and Writing Remediation on Educational Outcomes (Bandwidth: +/- 5 points)

	Short-term Impact			Long-term Impact		
	Dropped Out after the First Year	Took English Gatekeeper	Complete English Gatekeeper	Total Credits Earned in 5 years	Total College-Level Credits in 5 years	Earned Degree or Transfer to 4 yr univ in 5 yrs
Enrollment in Higher Level Reading Remediation						
Without Covariates	-0.040***	-0.034**	-0.023*	1.593**	-3.699***	-0.066***
	(0.011)	(0.010)	(0.013)	(0.698)	(0.654)	(0.011)
Covariates + IV	-0.001	-0.026	-0.010	2.495	-1.632	-0.098*
	(0.050)	(0.047)	(0.063)	(3.221)	(3.007)	(0.053)
Observations	9,039	9,039	6,054	9,039	9,039	9,039
Enrollment in Higher Level Reading Remediation						
Without Covariates	-0.025***	0.125	0.016	3.908***	-0.213	-0.046***
	(0.012)	(0.013)	(0.014)	(0.795)	(0.756)	(0.014)
Covariates + IV	0.020	-0.151	0.016	-6.181	-8.105	-0.098
	(0.096)	(0.105)	(0.088)	(6.283)	(5.948)	(0.107)
Observations	5,146	5,146	3,540	5,146	5,146	5,146

Notes: ***, **, and * denote statistical significant at 1%, 5% level, and 10% level, respectively. Each cell represents a separate regression using instrumental variable approach within a 10 point band. The instrumental variable model include college fixed effects and the following covariates: a gender dummy variable, race dummy variables, cohort dummy variables a dummy variable for receiving federal financial aid, a dummy variable for whether in a transfer program, a dummy variable for dual enrollment prior to college.

Table 3.4 Impact of Lower Level Reading and Writing Remediation on Educational Outcomes (Bandwidth: +/- 5 points)

	Short-term Impact			Long-term Impact		
	Dropped Out after the First Year	Took English Gatekeeper	Complete English Gatekeeper	Total Credits Earned in 5 years	Total College-Level Credits in 5 years	Earned Degree or Transfer to four-year University in 5 years
Enrollment in Lower Level Reading Remediation						
Without Covariates	-0.011	-0.110	0.008	0.620	-3.517***	-0.101***
	(0.020)	(0.019)	(0.027)	(1.200)	(1.065)	(0.019)
Covariates + IV	0.134*	-0.164**	-0.051	-10.802**	-9.567**	-0.144**
	(0.074)	(0.072)	(0.114)	(4.496)	(3.958)	(0.070)
Observations	3,122	3,122	1,620	3,122	3,122	3,122
Enrollment in Lower Level Writing Remediation						
Without Covariates	0.012	-0.177***	0.034	-2.310	-4.766***	-0.052**
	(0.025)	(0.025)	(0.034)	(1.540)	(1.382)	(0.024)
Covariates + IV	0.188*	0.019	-0.043	-8.509	-10.261*	-0.117
	(0.111)	(0.112)	(0.146)	(6.832)	(6.130)	(0.108)
Observations	2,027	2,027	1,056	2,027	2,027	2,027

Notes: ***, **, and * denote statistical significant at 1%, 5% level, and 10% level, respectively. Each cell represents a separate regression using instrumental variable approach within a 10 point band. The instrumental variable model include college fixed effects and the following covariates: a gender dummy variable, race dummy variables, cohort dummy variables a dummy variable for receiving federal financial aid, a dummy variable for whether in a transfer program, a dummy variable for dual enrollment prior to college.

Table 3.5 Heterogeneous Effects of Lower Level Reading Remediation by Subgroup (Bandwidth: +/- 5 points)

	Short-term Impact			Long-term Impact		
	Dropped Out after the First Year	Took English Gatekeeper	Complete English Gatekeeper	Total Credits Earned in 5 years	Total College-Level Credits in 5 years	Earned Degree or Transfer to four-year University in 5 years
Institution						
High Remed. College (N=1,060)	0.300** (0.120)	-0.226* (0.119)	0.069 (0.212)	-22.950*** (7.704)	-20.912*** (6.626)	-0.283*** (0.113)
Low Remed. College (N=858)	0.004 (0.125)	-0.142 (0.111)	-0.126 (0.179)	-7.525 (7.475)	-7.108 (6.798)	-0.062 (0.116)
Gender						
Female (N=1,933)	0.112 (0.091)	-0.265*** (0.088)	-0.181 (0.134)	-15.214*** (5.782)	-14.152*** (5.073)	-0.244*** (0.090)
Male (N=1,189)	0.181 (0.127)	0.011 (0.129)	0.254 (0.220)	-4.308 (7.324)	-2.612 (6.503)	0.018 (0.113)
Age When Started College						
Above or Equal to 25 (N=391)	-0.133 (0.282)	-0.154 (0.293)	0.311 (0.856)	-10.943 (15.016)	-7.051 (12.971)	-0.239 (0.244)
Below 25 (N=2,731)	0.186** (0.076)	-0.138* (0.074)	-0.091 (0.116)	-12.622*** (4.715)	-11.495*** (4.147)	-0.145** (0.073)
Race						
White (N=1,418)	0.171 (0.126)	-0.135 (0.121)	-0.042 (0.204)	-8.780 (8.057)	-7.997 (7.217)	0.015 (0.119)
Black (N=1,247)	0.076 (0.118)	-0.220* (0.116)	-0.019 (0.212)	-10.732* (6.502)	-9.358* (5.657)	-0.250** (0.109)

Notes: ***, **, and * denote statistical significant at 1%, 5% level, and 10% level, respectively. Each cell represents a separate regression using instrumental variable approach within a 10 point band. The instrumental variable model include college fixed effects and the following covariates: reading test score, a quadratic term of the testing score, a gender dummy variable, race dummy variables, cohort dummy variables a dummy variable for receiving federal financial aid, a dummy variable for whether in a transfer program, a dummy variable for dual enrollment prior to college.

FIGURES

Figure 1.1.1 Online and Face-to-Face Course Outcomes, 2004-05 to 2008-09

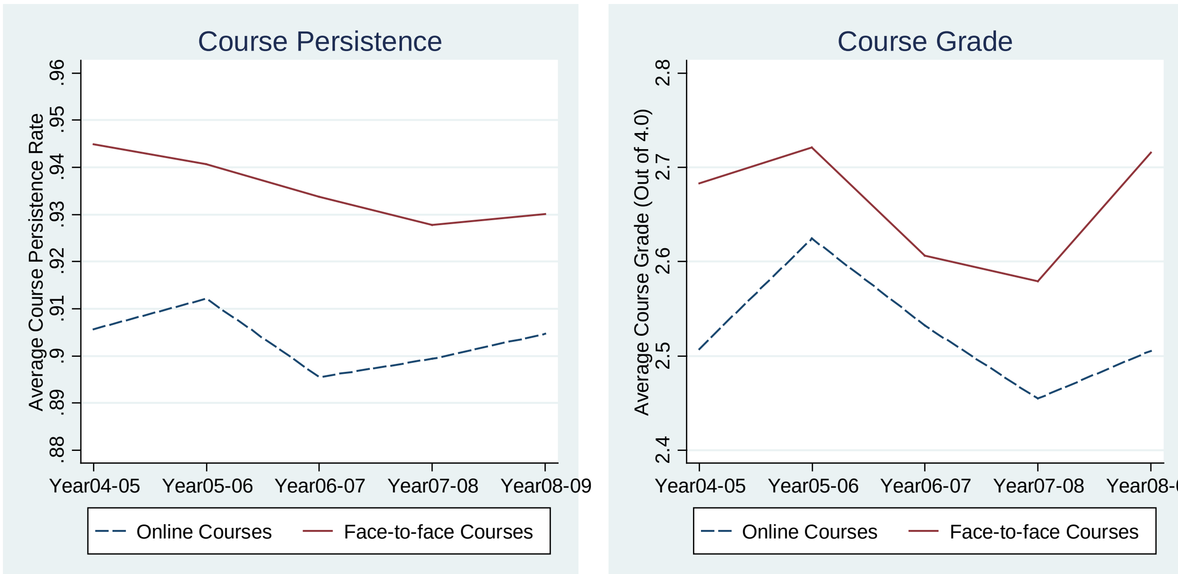
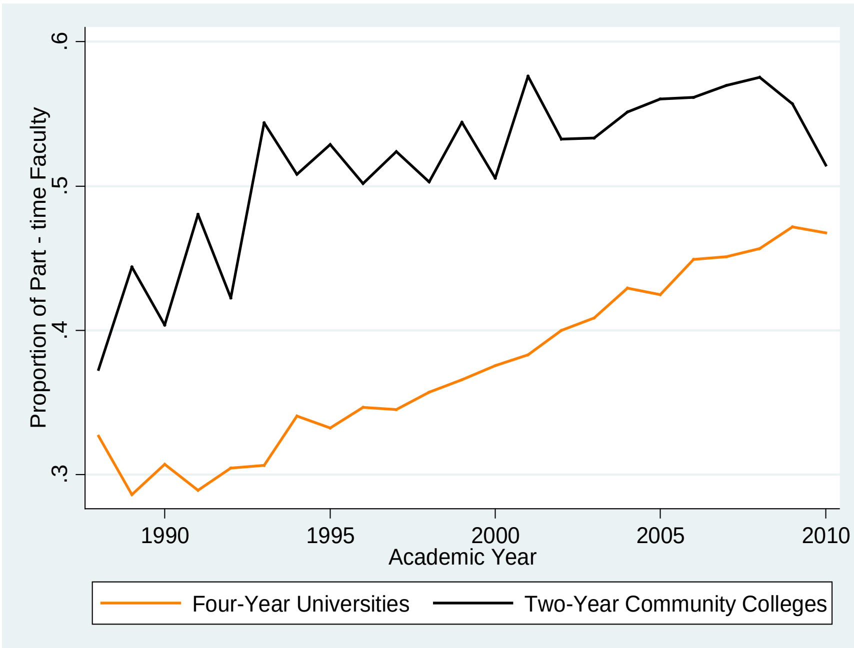


Figure 2.1 Changes of the Proportion of Part-time Faculty in Four- and Two-year Public Higher Education Institutions between 1988 and 2010



Data Source: IPEDS 1987-2010

Figure 2.2 Variations in Course Offerings by Adjuncts across Colleges and Fields

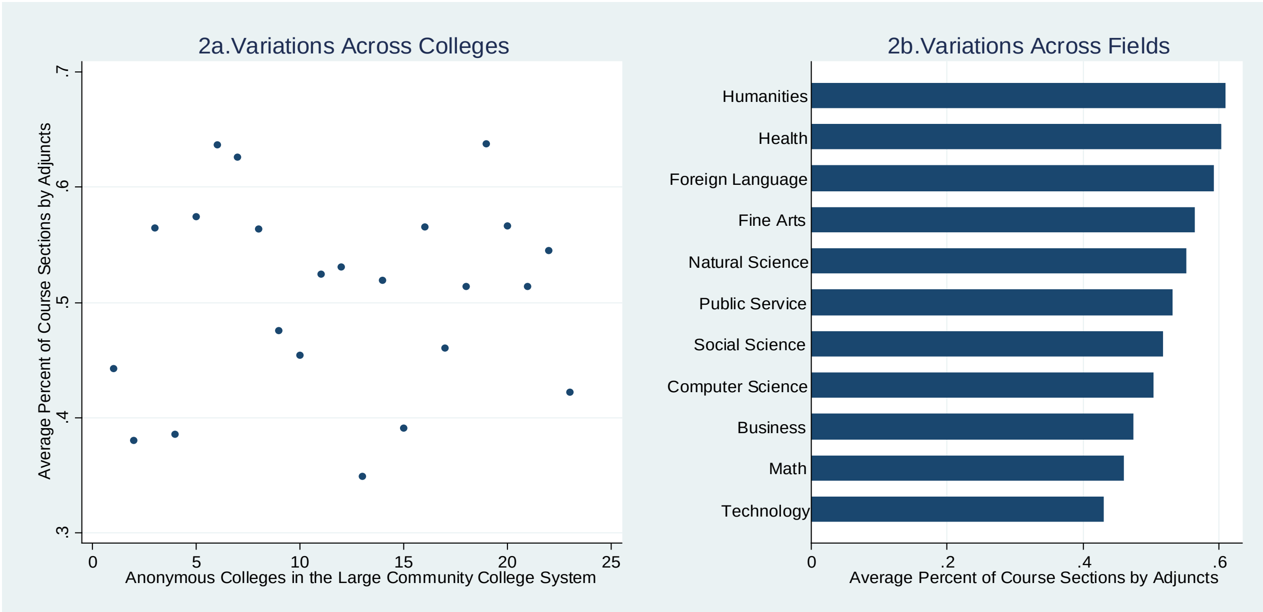


Figure 2.3 Variations in Course Offerings by Adjuncts across Time

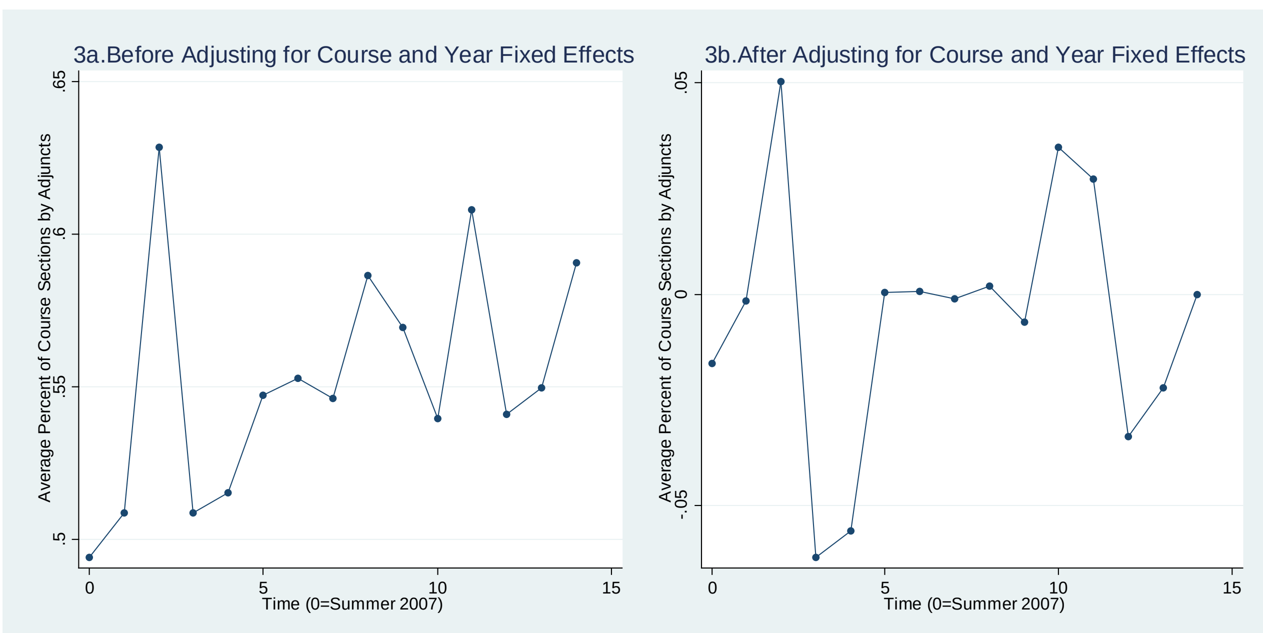
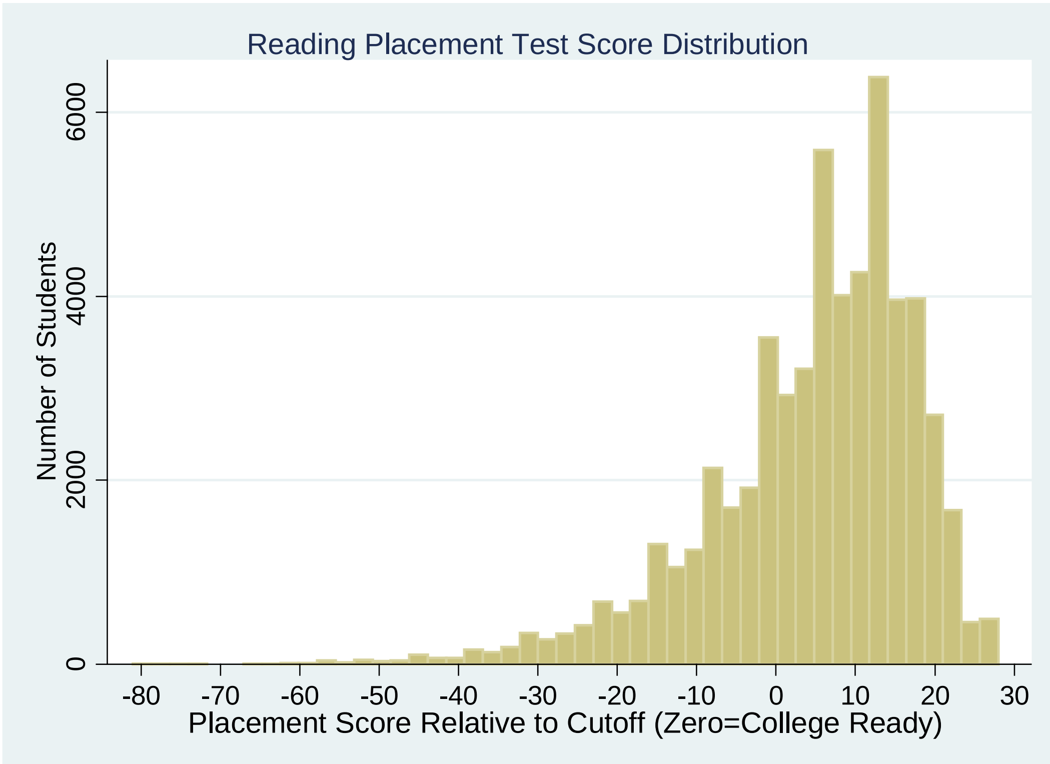


Figure 3.1 Distribution of Observations by Placement Scale Score



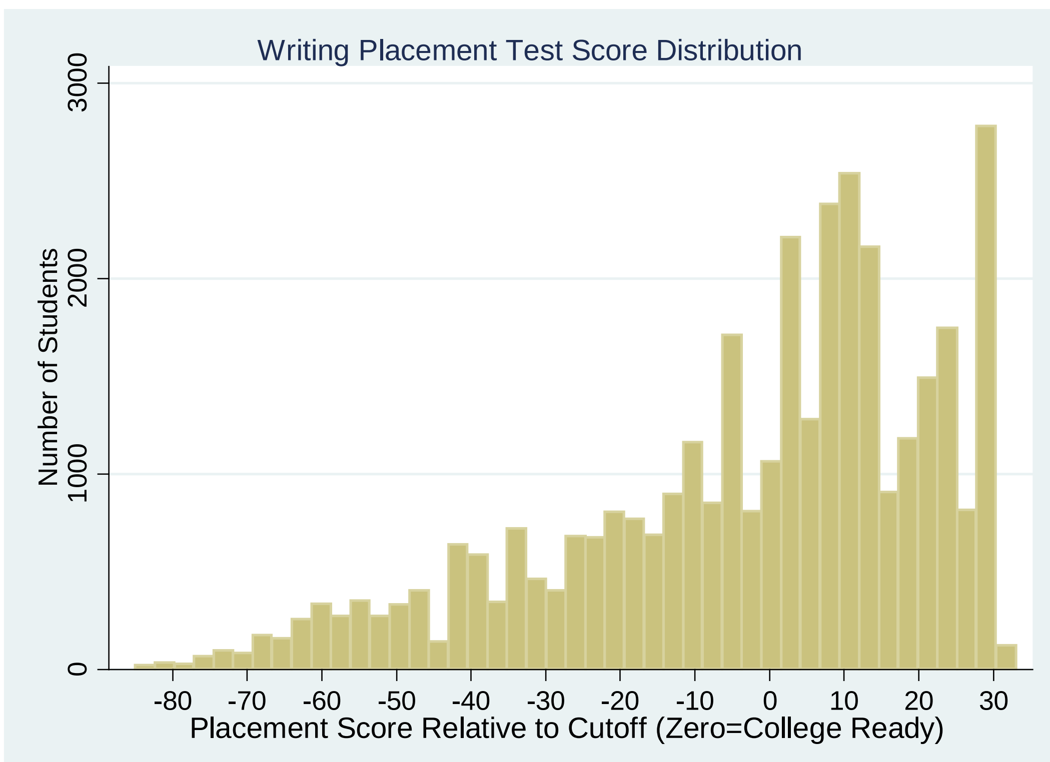
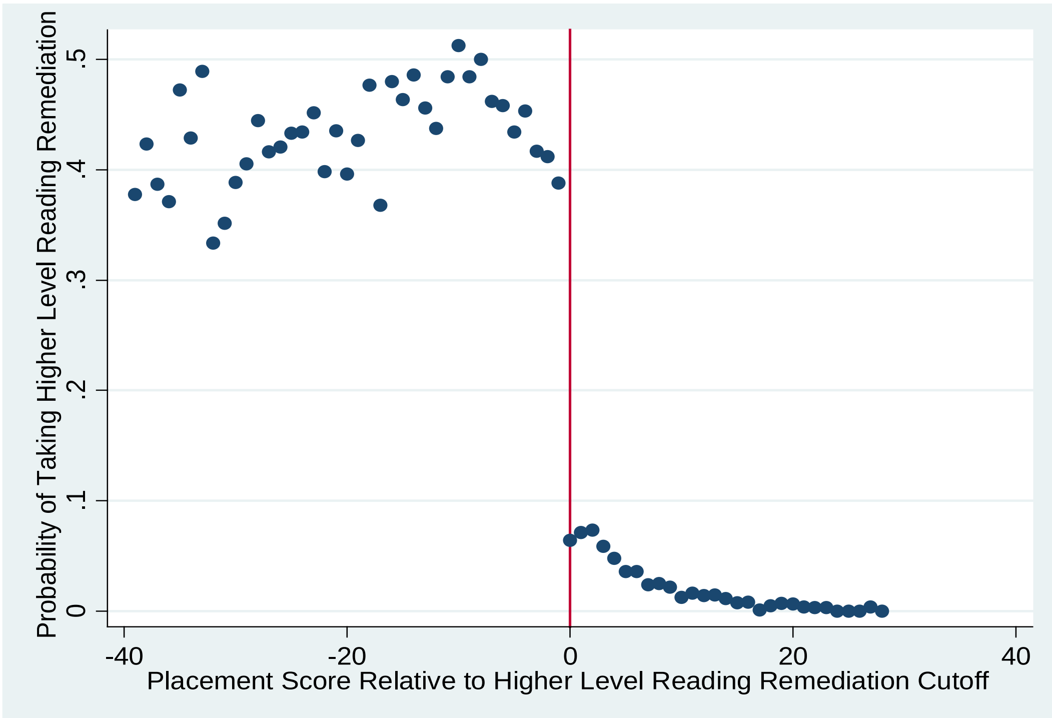
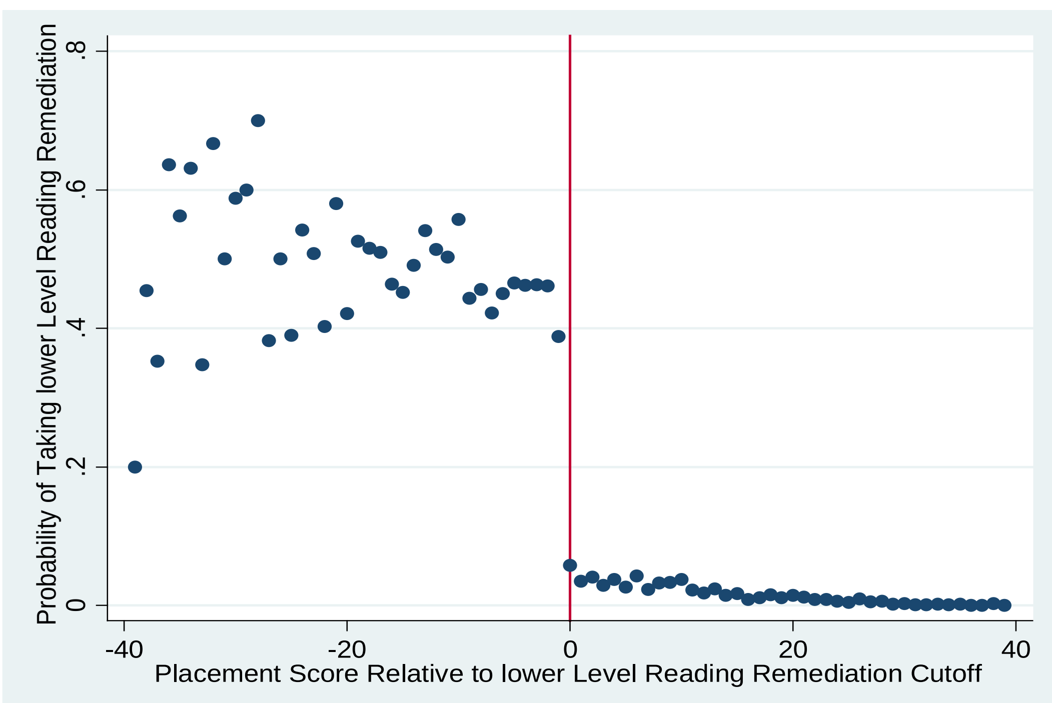


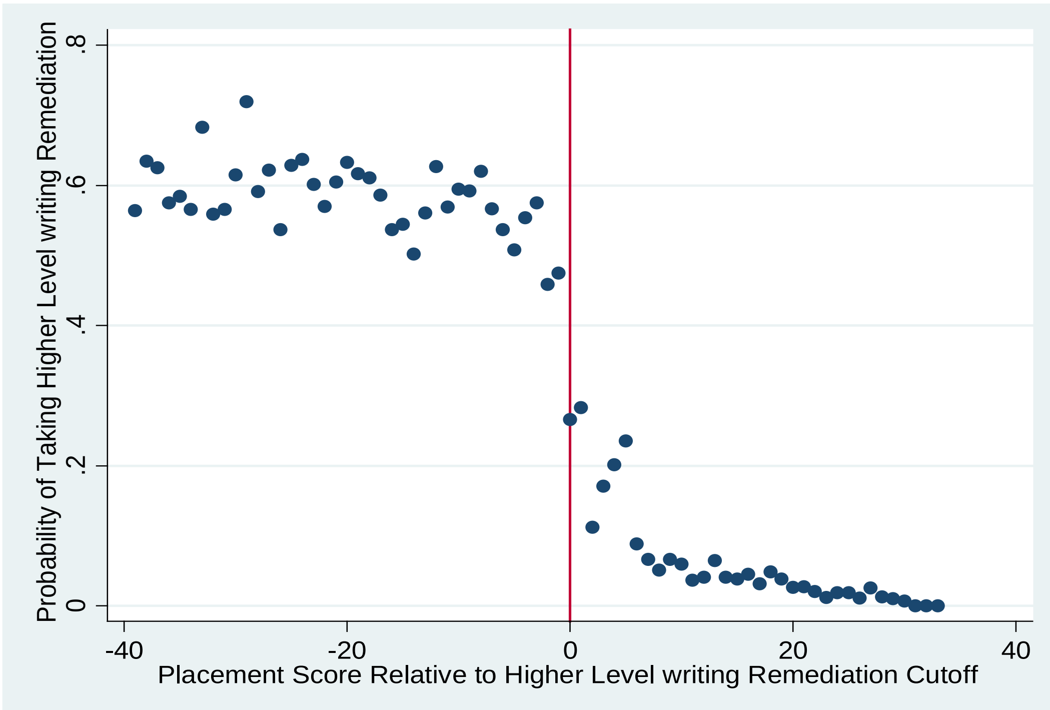
Figure 3.2 Probability of Remediation Enrollment by College Placement Test Scores
Higher Level Reading Remediation



Lower Level Reading Remediation



Higher Level Writing Remediation



Lower Level Writing Remediation

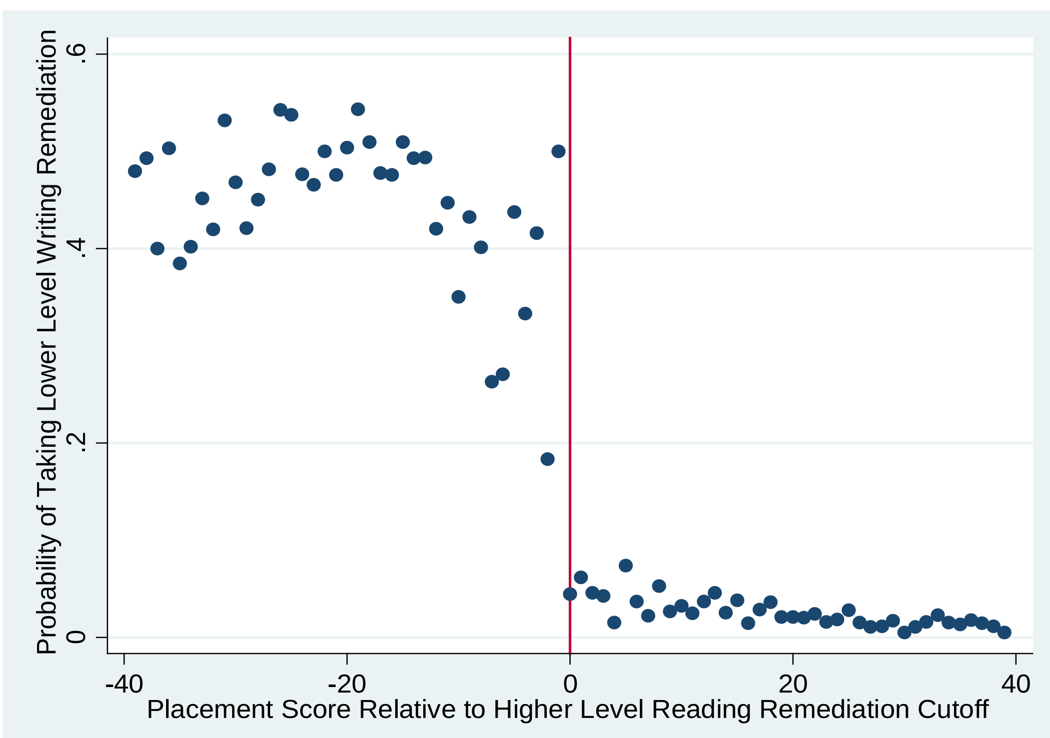
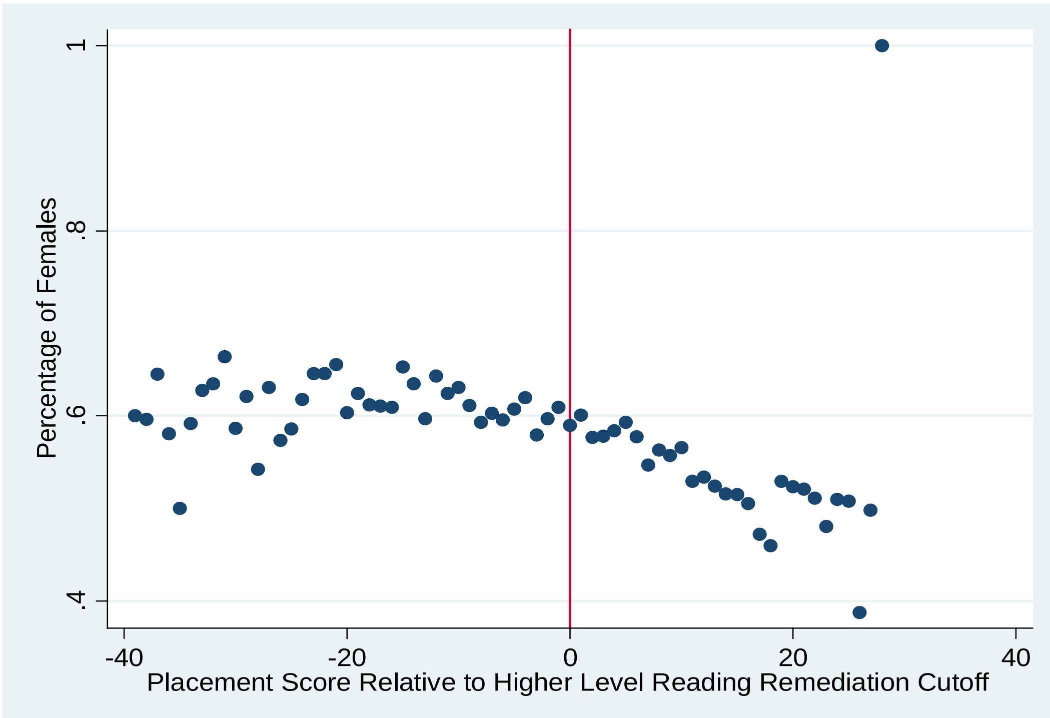
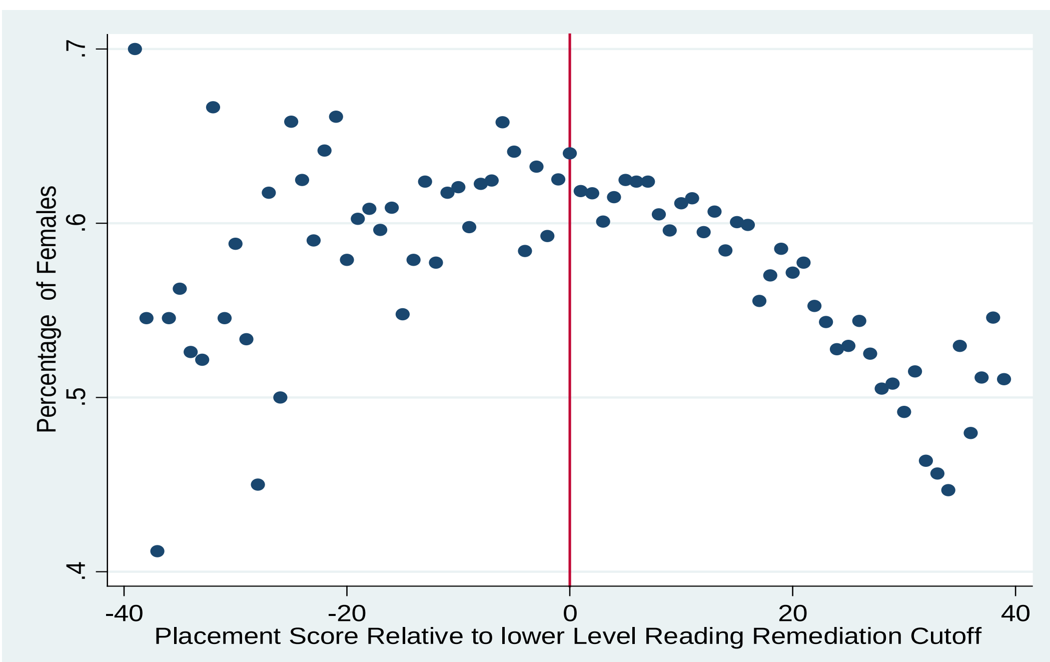


Figure 3.3 Placement Test Score Distribution by Gender

Higher Level Reading Remediation vs. College Ready Reading



Lower Level Reading Remediation vs. Higher Level Reading Remediation



Higher Level Writing Remediation vs. College Ready Writing

Lower Level Writing Remediation vs. Higher Level Writing Remediation