Does Online Credit Recovery in High School Support or Stymie Later Labor Market Success?

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Abstract

An emerging body of research links online credit recovery programs to rising high school graduation rates but does not find comparable increases in student learning. This study follows high school graduates who took courses online primarily for credit recovery into the labor market to understand the longer-term implications of this growing educational trend for their outcomes. If employers see high school completion as a signal that graduates have attributes that would make them good workers, then online credit recovery may facilitate job entry or have little effect on their labor market outcomes. However, if online credit recovery courses are inferior in terms of the knowledge or skills they impart and that learning is critical to workforce success, then online course-takers would be expected to earn less over time, as human capital theory predicts. The study findings suggest that high school graduates who took courses online to recover failed credits initially had earnings on par with or slightly lower than those who did not take courses online. But the gap (negative) between their earnings and those of students who did not take courses online grew over time, particularly for males. High school graduates who enrolled in college after taking online courses in high school saw relatively larger earnings gaps emerge relative to their peers who enrolled in college but did not take courses online, implying that any benefits of greater access to postsecondary education associated with high school completion through credit recovery might not pay off later in the labor market. Analyses with high school dropouts showed a similar pattern in their earnings following high school exit, with no associations suggesting that they benefitted in the labor market from online credit recovery.

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I. Introduction

The high school graduation rate, as Heckman and LaFontaine (2010: 244) asserted, is a "barometer of the health of American society," as well as a frequently used gauge of the skill level of the labor force. A half century ago, the U.S. high school graduation rate was highest among the Organization for Economic Co-operation and Development (OECD) countries, but until recently, it largely stagnated, and the U.S. fell behind most of its OECD peers (Murnane, 2013). This elicited a puzzle, given that the average economic returns to a high school degree were increasing over this same period, and also spurred more investigation into how high school graduation rates were being measured—including both who and what (e.g., General Educational Development, or GED, certificates) was counted. For example, estimates were found to be particularly sensitive to data and decisions used in calculating graduation rates for students of color, who are more likely to be GED recipients or recent immigrants (Heckman and LaFontaine, 2010; Murnane, 2013). Concerns about the accuracy of graduation rate measures were elevated when the No Child Left Behind (NCLB) Act of 2001 made them a key indicator of academic success in our federal and state public school accountability systems and mandated state reporting of high school graduation rates.

One explanation offered as to why U.S. high school graduation rates lagged in the latter decades of the 20th century is that students were not entering high school with the skill levels necessary to attain a diploma. Murnane (2013) showed that particularly for low-income, urban black and Hispanic students, enrolling for another year of high school was not resulting in an additional year completed. NCLB impelled states to reduce these racial and socioeconomic gaps in graduation rates and other achievement measures, specifying consequences for the lowest-performing schools and those with large and persistent achievement gaps. States were also required to adopt a uniform measure of high school graduation—the adjusted cohort (on-time, i.e., four-year) graduation rate—which became effective (mandatory) in the 2010-11 school year. The trend in U.S. graduation rates turned positive after 2000, increasing an estimated six percentage points between 2000 and 2010, and overall, achievement gains were larger among low-income students and those of color (Dee and Jacob, 2010; Murnane, 2013). However, despite the concerted efforts to place states and school districts on a level "playing field" in terms of standards and measures, research on NCLB implementation has cast doubt on claims that the accountability provisions of NCLB propelled real improvements in student learning and academic outcomes (Balfanz et al., 2007; Dee and Jacob, 2010).

Recent analyses of high school graduation rates using the uniform measure suggest that graduation rates have been increasing even faster since 2010, rising another six percentage points overall between the 2010-11 and 2016-17 school years (Gewertz, 2019). Moreover, the rate of increase was nearly double the average for black students (11 percentage points) and was larger for Hispanics (9 percentage points) and low-income students (8 percentage points) as well. Does this imply that these students are now attaining the skills required to satisfy high school graduation requirements? When a measure that has been relatively stable through decades of economic, social and education changes and reforms abruptly shifts following greater accountability pressures, we should be skeptical, argues Dynarski (2018), owing to Campell's Law.[1] Dynarski and others (Harris et al., 2020; Morgan et al., 2015; Hansen, 2017; Malkus, 2018) studying the rapidly rising graduating rates have identified a number of potential explanations, including substantive efforts to intervene earlier to help students stay on track for graduation (e.g., the Gaining Early Awareness and Readiness for Undergraduate Program, or

GEAR UP), as well as "shortcuts" such as providing alternate, easier options to complete their degree or "fudging" the numbers (e.g., removing students from graduation cohorts).

This study focuses on digital instructional programs known as "credit recovery," in which high school students repeat failed courses in an alternative (online) and sometimes abbreviated format. An emerging body of research links credit recovery programs to the rise in high school graduation rates but does not find comparable increases in student learning as measured by standardized test scores or end-of-course tests (Heinrich and Darling-Aduana, 2019; Viano, 2018; Viano and Henry, 2019). This study follows individual students who have engaged in online instruction for credit recovery—in some or all years of their high school education—into the labor market to understand the longer-term implications of this growing educational trend for their earnings and potential to achieve self-sufficiency. If, as some research suggests (Levin, 2009), high school completion improves non-cognitive outcomes among students in ways that enhance their labor market prospects (independent of test performance), making the attainment of a high diploma less costly through credit recovery could potentially improve these students' labor market outcomes. However, if high school course and degree completion through credit recovery is inferior to traditional classroom instruction in terms of students' cognitive and non-cognitive skills development, this could potentially devalue the high school credential in the labor market, to the further detriment of students directed to credit recovery programs.

At the same time, online course-taking typically offers high school students options for "anytime, anywhere" access to instruction, which may allow students to more flexibly balance employment with their schooling obligations. While the rate of employment among youth enrolled in high school averaged 20 percent in 2018[2], nationally representative data (from the National Longitudinal Survey of Youth) show that rates of employment are considerably higher among older high school students—more than a third of 10th graders and two-thirds of high school seniors typically combine work and school (Rothstein, 2007).[3] Concerns about high schoolers working outside of school pertain to the potential loss of hours for study time, increased absenteeism and poorer school performance, which might be only partially alleviated by online course-taking options (Quirk et al., 2001; Tyler, 2003; Rothstein, 2007). Especially for students heading directly to the labor market, however, working during high school could help them gain a toehold in the labor market, acquire “soft skills” and an understanding of workplace norms, and explore career opportunities. Rothstein (2007) also points out that we know little about how working in high school affects students’ choices in course-taking, their course progression, and how course enrollment and credits earned affect post-high school labor market outcomes. The rapid expansion of online credit recovery programs in U.S. high schools brings new attention to and heightens public interest in addressing these questions.

In undertaking this research, we draw on data assembled in a longitudinal study of the implementation of online instruction, primarily for credit recovery, in a large, urban school district in the Midwest. High schools in this district began offering online instructional opportunities in 2010, and by the 2016-17 school year, about 40 percent of graduating seniors had completed at least one course through the online course-taking system. Data from student school records were linked to data from the technology (credit recovery program) vendor to construct detailed, student-level measures of online and traditional course-taking in high school, from 2010-11 to 2017-18. These data were also linked to Unemployment Insurance records of student employment and earnings during and following their enrollment in high school, as well as to National Student Clearinghouse (NSC) data that provide information on student participation in postsecondary education. These data are used to test theory-informed hypotheses about the implications of online course-taking (to recover failed credits) for post-high school labor market participation and outcomes.

In the following section, we draw on theories of the economics of education and empirical evidence to develop expectations for the implications of online credit recovery programs (that potentially increase high school completion) for these young adults' post-high school labor market outcomes. We then describe the context of this study and the longitudinal data used, as well as the methodologies employed in the analysis. The findings suggest that high school graduates who took online courses in high school, particularly those who had failed a course and were recovering those credits online, initially had earnings on par with or slightly lower than those who did not take courses online, but the gap (negative) between their earnings and those of students who did not take courses online in high school grew over time. Analyses with high school dropouts showed a similar pattern in their earnings following high school exit, with no associations suggesting that they benefitted in the labor market from online credit recovery while in school.

II. Theory and Evidence Informing Expectations for Credit Recovery Program Effects

The market for credit recovery programs that provide an inexpensive (typically online) alternative for completing course credits required for high school graduation has proliferated in the past decade. Particularly for large, urban high school districts with greater numbers of students at risk for exiting high school without a diploma, credit recovery programs are believed to have contributed to substantial increases in their high school graduation rates, i.e., some more than 15-20 percentage points (Kirsch, 2017; Malkus, 2018; Heinrich and Darling-Aduana, 2019). Although empirical analyses confirm positive associations between online course taking for credit recovery and credits earned among upper classmen in high school, the research is fairly consistent to date in finding insignificant or negative relationships between participation in credit recovery and measures of student achievement, i.e., reading and math test scores (Heppen et al., 2017; Viano, 2018; Heinrich et al., 2019; Viano and Henry, 2019). Research that has looked into how students engage with credit recovery programs likewise questions whether students directed to complete their high school courses through credit recovery are learning in those courses (Heinrich et al., 2019; Darling-Aduana et al., 2019). Classroom observations revealed students frequently ignoring instructional videos and searching online for quiz or test answers rather than engaging with the course content; mismatches between student reading levels and the course content; inadequate language supports in the credit recovery program; high student-teacher ratios and limited teacher expertise with the course content, and low teacher expectations for student learning (Heinrich et al., 2019).

A. Human capital explanations and evidence

The ongoing theoretical and empirical debate about whether a high school diploma reflects gains in human capital (i.e., cognitive skills valued by employers), or rather is primarily a signal to employers who value other desirable (but unobservable) attributes among those completing secondary education is highly pertinent to concerns about high school credit recovery programs. Human capital theory predicts that time spent learning in school will directly increase labor market wages through its role in increasing worker productivity (Weiss, 1995). This suggests that if the way online credit recovery programs are implemented by high schools and used by students constrains their learning and acquisition of skills that employers value in the hiring process, students attaining their high school diploma through credit recovery programs could face poorer labor market prospects. On the other hand, some empirical research that has sought to test the theory that wages earned are causally associated with additional years of schooling—or that coursework matters for learning and later wages—has cast doubt on human capital explanations for returns to schoolings (Kang and Bishop, 1986; Altonji, 1995).

Acknowledging that most analyses of the relationship between education and wages assess the effects of *years of schooling*, Altonji (1995) alternatively used a national (1972) survey of secondary school curriculum that included measures of student semester hours in specific academic subjects in grades 10-12, as well as their earnings through 1985, to estimate the effects of coursework on their post-high school outcomes. He posed the question: how would students' post-high earnings be affected if rather than taking the standard course load, all course periods consisted of lunch or recess (essentially, a "social promotion")? Altonji adjusted for selection into courses using an instrumental variables approach, in which the high school averages of semester hours of each course taken (in a given subject) instrumented for the courses chosen by individual students in his sample (all of whom were high school graduates).[4] He found that an additional year of core instruction in science, math, English, social studies, and foreign languages would contribute to a small, statistically insignificant wage increase (i.e., only 0.3%), less than the value of a year in high school, with no subsequent improvement in wages over the 13 years following the students' high graduation.

Although decades have passed and curriculums have changed since Altonji's (1995) analysis, his findings have particularly important bearing on the investigation of credit recovery programs, because they suggest that at least for labor market outcomes, it may not matter if instruction is inferior or learning is limited in online credit recovery courses (relative to traditional high school course-taking). Weiss (1995) comments that these findings are especially remarkable because they reflect both the potential learning and signaling effects of the courses. The implication is that as long as students persevere through another year of high school, making attainment of a high diploma less onerous for students and less expensive for districts through credit recovery programs may come at little or no cost in terms of students' post-high school labor market outcomes. That said, Altonji did find that coursework in high school mattered for student success in postsecondary education. His estimates from instrumental variables (IV) models with controls for family background characteristics suggested that an additional year of math, science, and foreign language increased postsecondary educational attainment by about a third of a year. In addition, more recently, Gottfried and Plasman (2018) applied a similar IV estimation strategy as Altonji and found that high school career and technical education (CTE) course-taking increased the probability of on-time completion graduation from high school.

B. Sorting and signaling explanations and evidence

Sorting models, distinct from human capital theory, factor in individual productivity differences that are *correlated* with their choices in schooling but not are not directly determined by them. Employers are limited in the attributes they directly observe about a prospective worker's productivity, thus, they instead use the individual's education level (e.g., receipt of a high school diploma) to make inferences about characteristics they are not able to observe but which may be correlated with schooling decisions (e.g., motivation, perseverance, health, etc.). In this regard, sorting models allow for learning to play a role in returns to education, while focusing on the ways in which educational attainment serves as a signal or filter for expected productivity differences (Weiss, 1995). That is, to the extent that employers reward the attainment of a high school diploma beyond the contributions (to worker productivity) of any learning that has taken place, students who persist to achieve their diploma through credit recovery programs should similarly see the returns in their labor market outcomes.

Levin (2012) points out that while human capital theory has been generally interpreted to predict a close link between education (and the value of skills it imparts) and individuals' labor market earnings, Becker's (1964) conceptualization of human capital was broader, that is, extending beyond skills that would be measured via the standardized achievement tests used in public schools today. Indeed, the empirical evidence base reports mixed findings on the relationship between cognitive test scores and earnings; while Goldhaber and Özek's (2019) analysis concludes there is an abundance of evidence suggesting a causal link between test scores and later life outcomes, other research suggests that test scores account for little of the apparent relationship between high school completion and earnings (e.g., Murnane, Willett, Bratz, and Duhaldeborde 2001; Murnane, Willett, Duhaldeborde, and Tyler 2000). This leaves open the question of whether the negative associations identified between online credit recovery program participation and student test scores in high school will extend to wages earned after high school graduation (or to the earnings of high school dropouts who exit without a high school degree).

It is also possible that by making the attainment of the diploma less arduous through credit recovery (i.e., less time and effort), more students could be incentivized to complete a high school degree. Empirical evidence on the net public benefits of high school completion shows strong returns in the form of higher earnings, improved health, reduced crime and lower public program participation (Levin, 2012). In addition, online credit recovery programs, which allow flexible access to course-taking outside the regular school day, might open more opportunities for students to combine labor market participation with schooling. To the extent that engaging in work while attending high school contributes to the development of non-cognitive skills that are valued by employers—or signals to employers that students will have acquired these skills—this could be another pathway through which online course-taking (for credit recovery) potentially improves students' post-high school labor market outcomes.

C. Research hypotheses

In this study, measures of students' employment and earnings during high school and following their exit from high school are available for seven cohorts of students who attended high school in the study district since it rolled out a credit recovery program (for up to seven post-high school exit years). For the earlier cohorts of students, there are more quarters of post-high school employment and earnings available than for the later cohorts. In addition, because of labor restrictions on children under age 16, few students work in their first year of high school. Therefore, while we generally observe as many as four years (16 quarters) of earnings during high school (and additional years following high school), sample sizes of students with earnings in the fourth year (pre- or post high school) are noticeably smaller. As in Altonji's (1995) study, we first restrict the analysis sample to students who graduated from high school. We then extend our analyses to a subsample of high school dropouts.

Based on the theories and evidence discussed above, we expect students taking online courses (primarily for credit recovery) to have either comparable earnings or lower post-high school earnings than similar students who complete or exit high school without taking courses through credit recovery. Thus, the null hypothesis—predicting no difference in post-high school earnings between high school credit recovery participants and nonparticipants—conforms to the expectations set out by signaling or sorting theories. For high school graduates, employers would see high school completion as a signal that the students have other (less readily observed) attributes that will make them good workers, which may or may not be related to anything that they learned in their courses.

Alternatively, human capital theory would predict that if high school courses taken through online credit recovery are inferior in terms of the learning they impart, and if that learning is critical to workplace productivity, high school credit recovery participants would earn less in the labor market than students who do not complete high school courses through online credit recovery programs. However, because employers may not observe which students complete courses through online credit recovery versus in traditional classroom settings,[5] it is possible that initial post-high school earnings would not differ between these two groups. If, over time, employers observe that students who completed courses through credit recovery perform relatively more poorly on the job, we would expect their earnings to fall behind those of workers who had not completed online courses in high school over subsequent post-high school quarters or years. In addition, credit recovery program participants might work fewer quarters following their graduation from high school if they are less likely to retain jobs.

As also discussed above, taking online credit recovery courses could allow more flexible access to high school course instruction and facilitate students working more while enrolled in high school, thereby giving them a stronger "toehold" in the labor market. If the analyses confirm this relationship, one might expect students participating in credit recovery programs to gain access to post-high school employment more quickly (or to transition into the labor market seamlessly), and therefore, their initial work participation and post-high school earnings might be higher than high school students with no credit recovery program participation. That said, there is no basis for expecting the earnings growth rate of high school credit recovery program participants to be higher than that of nonparticipants, and thus, any initial, positive earnings differential between these two groups is likely to be only a short-term.

In testing these hypotheses, we also explore (for high school graduates) how students' post-high school pursuit of postsecondary education opportunities influences the relationship between high school online course-taking and labor market outcomes. In prior research, Heinrich and Darling-Aduana (2019) found a small, positive relationship between participation in online credit recovery programs and college enrollment for those with limited online course-taking, but they also found significantly lower four-year college enrollments and lower institutional quality among the colleges where credit recovery program participants enrolled.[6] Hence, we do not have firm expectations for whether students who enroll in college after high school are more or less likely to participate in the labor market. According to data from the National Center for Education Statistics (NCES), 58 percent of full-time students in the 2015-16 academic year worked either full- or part-time while enrolled in college, and 26 percent of all undergraduates (working either full- or part-time) had full-time jobs. In general, we would expect students who are enrolled in college to have lower labor market earnings, given that time spent taking college courses would restrict time available for work. However, an analysis by the Urban Institute[7] showed that compared to college students in the 1960s and 1970s—who in working 800 hours across the year at the minimum wage could earn enough to pay the tuition, fees and most room and board charges at the average public four-year college—the equivalent level of work participation today at the minimum wage would cover only 27 percent of the total published charges for a four-year college education.

III. Data and Samples

In the urban school district that is the site of this study, about one fourth of high school students take courses online (primarily for credit recovery) in a given year, up from approximately five percent of high school students in the first year (2010-11) that the online program was used. Across the 46 high schools in the district (during the study period), the proportion of students taking courses online varied considerably both between and within high schools over time (e.g., from zero to more than 93 percent). As discussed further below, school-level administrative and staffing decisions and the types of student bodies served were among the most important factors in determining which and how many students were directed to take courses online (Heinrich et al., 2019).

A. Study data

The school district provided school records for all high school students from the 2010-11 through 2017-18 school years. These include student demographic information, absences and suspensions, course credits earned, grade point average (GPA), ACT scores, and standardized test scores. In addition, we received data from the state department of education that identified high school dropouts among the student records. The student records were linked to data provided by the vendor of the online instructional program for this same period, with a match rate of about 85 percent.[8] This particular technology vendor provides online courses to school districts in all 50 states, primarily for credit recovery, including eight of the 10 largest districts in the nation (Clough, 2016). The vendor data include detailed information on students' online courses and their engagement with the online instructional system (for each session a student logged in), as well as measures of their course progress, completion and online course grades. The school district also provided data from the National Student Clearinghouse that include information on student participation in postsecondary education (for those who exited high school). In addition, data on school characteristics that are made publicly available on the district's website, including school type, geographic location and others, were also linked to the district-provided data.

An important contribution of this study is the linking of Unemployment Insurance (UI) records from the state workforce development agency on student employment and earnings both during high school and following their exit from high school (to the other linked data described above). Matches between the student records and UI data were identified for 98.8 percent of all high school students in this study. For each student, there are as many as four years of earnings records before high school exit, with a small number of students (less than 0.5%) having more than four years of in-school earnings records if they attended more than four years of high school. In addition, up to seven years of post-high school earnings data are available for each student, which varies according to the years in which the students entered and exited school. The UI records include total earnings per quarter, employment by quarter, and the number of employers the student worked for in a given quarter. These data were used to generate annual and quarterly measures of student earnings, the number of quarters worked in a year, and the number of employers students worked for using the quarter and year of a student's exit/graduation from high school as "time zero." For example, for a student graduating from high school in June 2014, the first year of post-high school earnings would start in July 2014, and the year beginning July 2013 and going through June 2014 would be the most recent year of in-school earnings. Thus, for this student, measures could be constructed for up to four years of in-school earnings and up to four years of post-high years of earnings with the currently available UI data.

B. Study samples

The study sample frame begins with all high school students in the study district who were enrolled sometime in the 2010-11 through 2017-18 school years. For the analysis of primary interest in this research—examining the labor market outcomes of students who participated in online course-taking for credit recovery—we focus first on the subsample of high school graduates (i.e., students for whom we were able to verify that they completed high school). Among the high school graduates, approximately 41 percent took a course online sometime during the years they were enrolled in high school (compared to 42% in the broader sample frame). Second, we further restricted the subsample of high school graduates to students who had failed at least one course during high school—about half of the high school graduates—in order to create a more similar comparison group for the credit recovery participants and reduce the threat of omitted variable bias in the analyses.[9] Lastly, we created a third subsample limited to high school dropouts, of whom about 47 percent took online courses in high school. Most of the dropouts (86%) failed a course during high school, and among those, 56 percent took at least one course online. Table 1 presents basic descriptive information on student characteristics for the full sample and the three subsamples used in the earnings analyses.

Because participation in online course-taking (primarily for credit recovery) was increasing over time in this study district, a higher proportion of online course-takers graduated in the more recent years (2015-17). This also suggests that these students will have comparatively fewer quarters of *post-high school exit* workforce participation and earnings. In addition to the timing of exit or graduation, missing data on the outcome variables (quarterly or annual earnings and employment) could also occur for one of the following reasons: (1) the individual moved out of the state; (2) the employer did not report earnings information to the state; or (3) the individual worked in the informal sector and did not report earnings. To investigate whether missing outcome data differed by treatment status (online course-taking), we created dummy variables for each post-high school year that indicate whether earnings data were reported for a given observation. We then estimated logistic regressions with the missing data dummies as the dependent variable to predict missing outcome data, including as covariates the treatment status indicator, high exit year dummies, and in separate models, the addition of student characteristics that are controlled for in the analysis. The results of these regressions show that when only controlling for the high school exit year, students participating in online course-taking are significantly less likely to be missing earnings data. However, when student characteristics controlled for in the analysis are added to these models, the treatment status (online course-taker) dummy is no longer statistically significant in these regressions. Below, we further discuss estimation of alternative models to further explore the implications of missing outcome data for our analysis.

IV. Methods and Descriptive Analysis

In this study, the treatment of interest—online course-taking for credit recovery—takes place during the students' high school years. Students can take courses online anytime from their freshman to senior (or additional) school years, although over time, the study district reduced the number of students taking courses online in their 9th and 10th grade years, as it was observed that these students were not well-prepared in terms of reading level or the self-regulation required for progression in online courses (Heinrich et al., 2019). In this research, we focus on understanding the post-high school outcomes of students who took courses online in high school, primarily for credit recovery. Prior work (Heinrich and Darling-Aduana, 2019) suggests that participation in online course-taking for credit recovery is associated with higher rates of high school graduation in this school district. We also estimated models to predict high school graduation (versus dropouts, or exits without a high school diploma) as an outcome of online course-taking for credit recovery, but as we describe below, the high school dropouts are very selective in terms of their characteristics, and thus, it was challenging to avert the threat of selection bias.[10]

A. Descriptive analysis of treatment and outcomes

The descriptive analysis pointed to a number of statistically significant differences between students taking courses online in high school and the comparison samples. Focusing on the two sets of columns for high school graduates in Table 1, descriptive statistics in boldface indicate that the difference between the treatment and comparison groups was statistically significant (confirmed in two-sample tests). There are fewer differences between the treatment and comparison groups when the sample is constrained to students who failed at least one course in high school. For example, among high school graduates, online course-takers are significantly more likely to be eligible for free lunch (about 7 percentage points higher) than students not enrolled in online courses, but the difference in free lunch eligibility is negligible when the sample is constrained to those who failed at least one course in high school. Although it was speculated that enrolling in online courses (which allows students to perform their coursework outside the school day) might increase students' availability for labor market work and their workforce participation, among the high school graduates, there are no statistically significant differences in students' rate of workforce participation (quarterly or annually) while enrolled in high school by whether students took courses online. Alternatively, high school dropouts have considerably lower rates of workforce participation while in high school (compared to graduates), and dropouts who take course online have statistically significantly higher rates of workforce participation than those who do not. In general, when examining high school dropouts versus graduates or comparing online course-takers to those who did not take courses online *among dropouts*, there are many more statistically significant differences, reflecting how highly selective the dropouts are among those in our sample. Still, Figures 1a and 1b show largely parallel trends in (quarterly) earnings during high school between online course-takers and those without online courses, regardless of whether the sample is restricted to high school graduates.

Table 2 presents descriptive information on the earnings outcomes of high school graduates and dropouts (by treatment status) following high school exit and indicates the percentage of cases each year with UI data on earnings. For the reasons described above (students exiting high school later in the study period, and potentially, absence of employer earnings reports or work in the informal sector and moves out of state), the number of cases in each subgroup available for analysis declines each year. This table also distinguishes reports of *zero* earnings from the absence of reported earnings. High school dropouts have higher rates of zero reported earnings in every year, although over time, this proportion declines. For high school graduates, about six percent each year have zero reported earnings, with the exception of the graduates who did not take courses online in high school in their first year following graduation, of which a higher proportion (about 20% more) were enrolled in college. High school graduates who were online course-takers in high school initially had higher earnings on average than the comparison group, but by year three after graduation, the earnings of graduates who did not take courses online (and who also were more likely to enroll college) overtook those of the treatment group. Table 2 also shows that the average reported earnings of high school dropouts are less than half of those of high school graduates, yet among the dropouts, those who took courses online in high school had higher earnings than those who did not.

Figures 2a, 2b and 3 present the descriptive trends for student annual earnings both during and after high school graphically, including three years during high school and five years post-high school, for students with earnings data available in those years. Figure 2a presents these trends (by online course-taking) for high school graduates, while Figure 2b presents these same descriptive trends for all high school graduates compared to high school graduates who failed a course in high school. Figure 3 presents student annual earnings during and after high school (by online course-taking) for high school dropouts. These graphs confirm the parallel trends in pre-graduation earnings for both subsamples of high school graduates, and they also show the pattern of diverging earnings trajectories post-high school between online course-takers and those who did not take courses online (see again Figures 2a and 2b). In the first year post-high school graduation, average earnings for online course-takers are slightly above those who did not take courses online, but by the third year post-high school, the average earnings of those who did not take courses online in high school overtakes those of the treated (online course-takers). For high school dropouts, the earnings of online course-takers versus those not enrolling in online courses begin to diverge before high school exit (difference is statistically significant in the year prior to exit), and a steady gap persists until the fourth year after high school exit, when their annual earnings converge again. Of course, these descriptive trends in earnings do not take into account the differences between those who took courses online and those who did not, which we adjust for in the estimation of the effects of online credit recovery (discussed in the next section). In addition, given the declining numbers of cases with earnings data available five years post high school (as shown in Table 2), we urge some caution in interpreting the results of analyses using the fifth year of post-high school earnings.

B. Estimation approaches

In estimating the relationship between online course-taking for credit recovery and student outcomes, we adjust for selective differences between students who took courses online in high school and those who did not. While the ordinary least squares (OLS) regressions are estimated with controls for the covariates shown in Table 1, this will not address the potential problem of selection on unobservables and allow for causal inferences. To get closer to plausibly causal estimates, we employ an instrumental variables (two-stage least squares, 2SLS) approach to estimation, similar to Altonji (1995) and Rose and Betts (2004). Like Altonji, we use variation across high schools in the average number of courses taken by students in each high school—focusing on specialty courses (e.g., advanced, work-study, service learning, CTE) and the percentage of online course-takers in each high school—as well as average (school-level) student characteristics, to identify the effects of online course-taking for credit recovery. The intent is to purge the portion of course selection that is correlated with student abilities.

Both across and within schools, there was substantial year-to-year variation in the percentage of students taking courses online, even when the proportion of students failing their courses (the most influential predictor of online course-taking) varied negligibly. Interviews with district staff and teachers suggested that school-level administrative and staffing decisions and types of student bodies served were among the most important factors determining the incidence of online course-taking (Heinrich et al., 2019). For example, in one school where there were noticeably large year-to-year changes in student online course-taking, we learned that a new school principal wanted to understand more about the online course-taking program before committing instructional space for its use, and hence in her first year, only students who hadn't completed their online courses in the prior year were allowed to continue with the program (contributing to a steep decline in the rate of student online course-taking that year). We also inquired in an interview with the credit recovery program coordinator as to whether students were able to choose between credit recovery online and repeating a course in a traditional classroom, and also whether they could refuse the online option if they were assigned to it. The program coordinator explained that both schools and students generally preferred the online option for credit recovery. It was more costly for schools to place students in traditional classrooms to repeat a course, and as the credit recovery program coordinator indicated, "very few students" preferred the traditional classroom route, because it was a semester-long course. Alternatively, in the online credit recovery option, students could test out of course modules and work at a faster pace (including outside the regular school day) to complete courses sooner. In fact, our empirical analyses (Heinrich and Darling-Aduana, 2019) showed that school-level characteristics—including school-level demographics, course offerings (advanced, career and technical, service learning) and school type (alternative, charter, etc.)—accounted for more than two-thirds of the explained variation in online course-taking, while individual student attributes, including course failures, accounted for less than one-third of the explained variation.

As shown in equation 1 below, online course-taking (O_{is}) for student *i* in school *s* is predicted in the first stage, using the instruments for course offerings (C_s) and other school-level characteristics, Z_s(measured in the baseline school year for online course-takers or the 9th grade year for those not taking courses online). The predicted measures of online course-taking are then included in the second stage model (equation 2) to estimate the causal effect of online course-taking on student outcomes (Y_{is}):

$$O_{is} = \pi_0 + X_i\pi_1 + Z_s\pi_2 + C_s\pi_3 + \phi_s\pi_4 + \rho_t + e_{1is} \qquad (1)$$

$$Y_{is} = \delta_0 + X_i\delta_1 + Z_s\delta_2 + O\text{-}hat_{is}\delta_3 + \psi_s\delta_4 + \eta_t + e_{2is} \qquad (2)$$

where Z_s are school-level characteristics in a given year (e.g., administrative type, percent black, free-lunch eligible, English language learners, students with special needs, etc.), C_s is the average number of specific types of courses (e.g., advanced, work-study, service learning, and CTE) taken by students in high school *s* in a given year, ϕ_s is the proportion of students in school *s* taking courses online in a given year, and ρ_t is the year of high school graduation or exit. In the second-stage model, δ_3 is the estimated causal effect of online course-taking on student outcomes

(Y_{is}), ψ are school-level characteristics, and η_t is the graduation year. Following each 2SLS estimation (specifying robust standard errors), Wooldridge's robust score test of overidentifying restrictions and test for endogeneity are performed to assess if the estimating equation is correctly specified or the instruments are uncorrelated with the structural error term.[11]

The 2SLS IV models are estimated for (1) all high school graduates and (2) for the subsample of high school graduates who failed a course during high school, for each post-high school year of earnings. These models are then estimated for high school graduates who ever enrolled in college and for those who were not observed enrolling in college during the study time period, as well as separately for males and females, given historical differences in the rate of labor force participation and earnings between males and females. The 2SLS IV models are also estimated on the subsample of high school dropouts, including by gender.[12] Ordinary least squares regression models are likewise estimated for each of these subsamples (for comparison with the IV model results).

The first-stage IV model results consistently show that the average number of advanced, work-study, service learning and CTE courses taken by students (across schools), school type and the proportion of students taking courses online in a given school and year are strong, statistically significant predictors of online course-taking (primarily for credit recovery). Students who enrolled in CTE courses, for example, were significantly less likely to take online courses, even among the subsample who failed a course in high school. Average (school-level) student characteristics, including the proportion black, free-lunch eligible and with special educational needs, were also strong predictors of online course-taking in most models. The first-stage model F-statistics ranged from over 400 in the estimation with high school graduates and earnings in the first year post-high school as the outcome, to approximately 40 in models with the restricted subsamples (i.e., students who had failed a course in high school and enrolled or not enrolled in college) predicting later earnings outcomes (with fewer observations); even the lower F-statistic values exceeded the thresholds suggested by Stock et al. (2002) for strong instruments. With only a few exceptions, in estimations with smaller, restricted samples (noted in the results tables), the Wooldridge's robust score tests of over-identifying restrictions and endogeneity did not reject the null hypothesis, suggesting the models were correctly specified and the instruments were uncorrelated with the error term. First-stage model results for two of the primary analytic samples (high school graduates and the subsample of graduates who failed a course in high school) are shown in Appendix A.

V. Study Findings

A. Results for high school graduates

We begin by presenting a summary of the estimated effects of online course-taking for credit recovery from the 2SLS IV models and OLS regression models for high school graduates in Table 3. Focusing first on the sample of all high school graduates, the general pattern of effects shows no statistically significant differences in earnings between online course-takers and students with no online course-taking in high school *in the first two years post-graduation*. Table 3 also shows, however, that the trend is toward an increasingly negative effect of online course-taking on earnings, which becomes larger and statistically significant by the third year post-graduation (in both the OLS regression and 2SLS IV models). When the study sample is restricted to the subsample of students who failed at least one course in high school (about half of all high school graduates), the pattern of results is similar, and the estimated effects are all negative in sign, although not statistically significant. Figure 4 presents these results graphically.

1. Estimated effects by college enrollment. As indicated above, the OLS regression and 2SLS IV models were also estimated separately for high school graduates who ever enrolled in college and for those without any college enrollment, recognizing that the patterns might be different for students who were pursuing postsecondary education. These estimated effects of online course-taking are shown in Table 3 for the sample of all high school graduates and the subsample of students who failed at least one course in high school, and the results are also presented graphically in Figure 5. They indicate that the negative effect of online course-taking for credit recovery in high school is considerably larger for those *who enrolled in college* after high school. The estimated annual earnings difference for these young adults is statistically significant and greater than −$3,000 in the third and fourth years following high school graduation (compared to those who did not take online courses in high school but likewise enrolled in college after graduation), and the gap by the fifth year post-high school exceeds −$6,000. The results estimated with the subsample of students who failed a course while in high school and enrolled in college after graduation show a very similar pattern in the effects of online course-taking on earnings, turning increasingly negative and statistically significant by the third year post-high school. The OLS estimates of online course-taking by college enrollment (for all high school graduates and the subsample who failed a course in high school) likewise show the same patterns in effects, although the estimates are not statistically significant (see Appendix B). In related research, Heinrich and Darling-Aduana (2019) found that students who took courses online in high school (versus those who did not take courses online) enrolled in poorer quality postsecondary institutions that were more likely to have open admissions and lower average retention and completion rates. The findings depicted in Figure 5 suggest that any small increase in college enrollment associated with online course-taking in high school identified in their research may not ultimately lead these students to improved long-term earnings trajectories.

2. Estimated effects by gender. In light of enduring differences between males and females in labor force participation and postsecondary education pursuits, the 2SLS IV models were also estimated separately for males and females, beginning with subsamples of high school graduates and high school graduates who failed a course during high school. The estimated effects of the analyses for high school graduates by gender for these two subsamples are shown in Table 4 and graphically in Figure 6. The results show similar patterns in post-high school graduation earnings for male and female online course-takers, turning negative (or more negative) after the first two years post-high school, although males fared more poorly in their labor market earnings compared to females. Table 4 also reports the estimated effects of high school online course-taking for credit recovery for males and females by college enrollment, and these results are presented graphically in Figure 7. Again, online course-takers who enrolled in college after high school graduation had greater (negative) gaps in post-high school earnings relative to those who did not take courses online, and these gaps were especially large (and statistically significant) five years after graduation for males who enrolled in college (i.e., more than $9,000 *less* in annual earnings). Among the high school graduates who failed at least one course in high school and took courses online, females who did *not* enroll in college had the most favorable post-high school earnings trajectory compared to those who did not take courses online (see Figure 7).

3. Estimated effects on employment. To better understand the observed post-high school earnings differences between students who took courses online in high school and those who did not, we also estimated the number of quarters they worked in the first two years after exiting high school. A little more than one third of the young adults in the sample worked in all eight quarters after leaving high school. The estimated effects of online course-taking on employment for high school graduates, as well as for the subsamples of graduates who failed a course and who enrolled (or did not enroll) in college, are displayed graphically in Figure 8. The 2SLS IV analysis results suggest that online course-taking is positively associated with the number of quarters worked for high school graduates, although only one estimate is statistically significant (for all high school graduates); this estimate suggests that online course-takers worked about 0.2 (or one-fifth) of a quarter more in the first two years after graduating from high school. Figure 8 also reports the estimated associations with quarters worked for the subgroup of high school dropouts who took courses online in high school. This is the only subgroup for which online course-takers were less likely to be employed in the first two years after high school exit (compared to other high school dropouts who did not take courses online), although this estimated association was also not statistically significant. Additional analyses that estimated the relationship between online course-taking in high school and the number of quarters worked in three and four years post-high school did not reveal any statistically significant relationships. These findings suggest that the negative differential in estimated earnings for online course-takers (that appears primarily after the second year post-high school) may be more likely driven by lower wages received on the job than by less workforce participation.

B. Results for high school dropouts

The table in Appendix C presents results from IV models estimated on the subsample of high school dropouts. For reference, this table also presents the estimated associations of online course-taking with labor market outcomes for all high school exiters (graduates and dropouts) and for all high school exiters who failed a course in high school. The bottom panel of the table presents the estimated effects separately by gender. In addition, Figure 9 presents the results graphically from the IV models that estimated the associations of online course-taking with post-high school earnings for the subsample of dropouts, and for comparison, results for high school graduates, all high school exiters and high school exiters who failed a course in high school are also shown. The estimated associations of online course-taking with earnings for dropouts are always negative in sign, and the outcomes worsen after two years following high school exit, with a statistically significant, estimated earnings gap of more than −$4,500 by the fifth year after high school. Although these associations are comparable in magnitude to those for all who exited high school, the size of the (negative) gap is largest by the fifth year for the dropouts. The results for dropouts by gender suggest that female dropouts who took online courses in high school initially appeared to fare more poorly in the labor market (relative to dropouts without online course-taking) than male dropouts did relative to their counterparts, but by the fourth and fifth years after exiting high school, both female and male dropouts have substantially lower earnings than dropouts who did not take courses online for credit recovery in high school.

The descriptive statistics on post-high school outcomes shown in Table 2 indicated that dropouts typically earn about half as much annually as high school graduates in the labor market. As noted earlier, because of the considerable observed (and likely unobserved) differences in the characteristics of high graduates and dropouts, we were unable to overcome selection bias in our efforts to estimate whether online course-taking in high school would affect the likelihood a student graduated (versus dropped out) from high school. In addition, as Gottfied and Plasman (2018) point out, the rate at which students drop out of school increases in the later high school years, which is also the time (11^{th} and 12^{th} grade) when students are more likely to repeat failed courses online (and use the online course-taking system more productively) (Heinrich et al., 2019). Thus, it is not surprising that our estimated associations between online course-taking and earnings for the subsample of high school dropouts imply that they do not benefit from this form of credit recovery (relative to those who did not take online courses) in their employment and earnings trajectories following exit from high school.

C. Estimated effects adjusting for missing data on outcomes

The samples sizes reported in Table 2 confirm that the number of earnings records available decreases with each year post-high school, largely because later earnings data are not available for students graduating in more recent school years. However, as we also noted, UI earnings data could be missing because the student moved out of the state after graduation or worked in the informal sector, or the employer didn't report earnings information. The analyses discussed above suggested that students who took courses online in high school for credit recovery were less likely to be missing data, possibly associated with lower mobility; however, after adding control variables (for student characteristics) to the models, these differences diminished and were mostly no longer statistically significant. Existing research suggests that workers in sectors with no or partial coverage in UI data represent about 10 percent of U.S. employment (Kornfeld and Bloom 1999; Hotz and Scholz 2002). Estimates of employers or workers neglecting to report earnings associated with self-employment or the "gig economy" or flexible staffing arrangements are harder to estimate, although Abraham et al. (2018) suggest that administrative data are less likely to miss these newer types of self-reported earnings than survey data.

In Table 5, the estimated effects of online course-taking on post-high school earnings are presented for models in which missing earnings data were replaced with zeros (assuming no earnings for a quarter in which earnings were missing), and a dummy variable was added to the models to indicate when an observation was missing a value for earnings (i.e., separate dummies for missing either the post-high school earnings outcome or the in-school earnings control variable). The results show essentially the same patterns in estimated effects and statistical significance of the estimates. As expected, the magnitudes of the effects are smaller, and more so for the later year estimates (where more missing data were replaced with zero earnings values). These same patterns in estimated effects also emerge by whether the students ever enrolled in college after graduating. High school dropouts again appear to fared most poorly through online course-taking for credit recovery.

Recent research by Foote and Stange (2019) examines the bias that potentially occurs in estimating earnings outcomes using administrative data with missing values, particularly missing data associated with individual moves out of state. They use the U.S. Census Longitudinal Employer-Household Dynamics (LEHD) data that include UI earnings records from all states and the District of Columbia, in combination with state UI data from Colorado and Texas, to compare the results of analyses that use in-state earnings records to those using the national records. Focusing on a college-going sample, they find that out-of-state migration is a larger problem for high-earners, flagship graduates, and business majors, which is minimally applicable to the sample used in estimation for this study. Foote and Stange furthermore conclude that any bias present is more likely to be reduced by constraining the sample to those with positive observed earnings (vs. simply assuming those missing data are not working), as we have done in producing the primary estimates for this study.

VI. Discussion and Conclusion

In framing this analysis based on theory and existing research evidence, one of the hypotheses we set forth is that students taking courses online for credit recovery would likely have either comparable earnings or lower post-high school earnings than similar students who completed high school without enrolling in online courses, in accord with the expectations set out by signaling or sorting theories. For those graduating from high school, at least initially, employers would likely see high school completion as a signal that the graduates have attributes (some less readily observed) that would make them good workers, which would not necessarily be related to anything that they studied or learned in their high school courses. However, if it was the case that high school courses taken online for credit recovery are inferior in terms of the knowledge or skills they impart, and if, as human capital theory suggests, this learning is critical to their success in the workforce, then we would expect that this would affect their earnings over time. More specifically, students taking courses online in high school for credit recovery would earn less over time if employers observed that they performed more poorly on the job. Indeed, this causal story is consistent with the evidence generated in this study. Students (both males and females) who took online courses, especially those who previously failed a course and were recovering those credits online, saw the gap (negative) between their earnings and those of students who did not take courses online grow over time.

In addition, high school graduates who enrolled in college after taking online courses in high school saw relatively larger earnings gaps emerge relative to their peers who enrolled in college but did not take courses online, implying that any benefits of greater access to postsecondary education associated with high school completion through credit recovery might not pay off later in the labor market. As noted above, prior research suggests that students who took courses online in high school enrolled in poorer quality postsecondary institutions. In addition, our analyses (separately) for high school dropouts showed similar patterns of negative associations between online course-taking and earnings (following their exit from high school) that grew in magnitude over time, again implying no benefits were realized in the labor market from online credit recovery.

These findings resonate with those of earlier analyses of the GED (Cameron and Heckman, 1993:1), which concluded that there is "no cheap substitute for schooling." Cameron and Heckman compared those who completed high school through the GED (exam-certified high school equivalents) with traditional high school graduates and examined their subsequent wages and hours of work and postsecondary education participation. Adjusting for selective differences between GED recipients and high school graduates, they similarly found that the wages of (male) GED recipients were significantly lower than those of high school graduates and were closer to those of high school dropouts. They likewise found that while passing the GED might open postsecondary education and training opportunities, GED recipients who enrolled in postsecondary schooling and training earned lower wages than high school graduates who pursued postsecondary educations.

This is the first study we know of to follow students taking courses online in high school, primarily for credit recovery, into the labor market. Drawing on existing research and estimates of program costs from the school district that is the site of this study, Heinrich and Darling-Aduana (2019) calculated that credit recovery programs are approximately 25 to 100 times less expensive than other interventions known to increase graduation rates. School districts also value these programs because they help them to avoid the loss of state funding that occurs when students drop out of high school or leave for alternative programs outside the district, although we did not observe any benefits of online credit recovery for students who subsequently drop out, and we were unable to determine if participation in credit recovery programs reduces dropouts. These findings suggest that caution and reflection are in order for the large urban school districts that have increasingly turned to online credit recovery programs as an inexpensive alternative to helping high school students who are falling behind in their progress toward graduation to recover course credits and complete high school. Although their earnings are largely on par with (or only slightly less than) their peers who do not take courses online in the first years after high school, the results point toward a growing earnings gap over time. If these patterns in earnings outcomes for online credit recovery program participants were more widely confirmed, they may suggest the potential for online credit recovery programs to reduce the value of the high school degree in the labor market.

Lastly, there are some important limitations of this research that need to be acknowledged or reiterated. First, the findings are based on data from a single, large urban school district, and while it shares many characteristics with other large urban school districts using this same online instructional program (e.g., high poverty rate, largely serving students of color, and low resources), we do not make claims about the generalizability of these findings to similar school districts in the U.S. In addition, although 2SLS IV strategy for empirical estimation appeared to work well in adjusting for student selection into online course-taking in this district, threats to validity associated with unobserved characteristics of the study sample and the missing outcomes data suggest caution is warranted in drawing conclusions about point estimates and longer-term earnings trends from the analysis. In addition, given the highly (negatively) selective characteristics of the high school dropouts included in some of our analyses, we interpret those estimates as associations rather than plausibly causal effects.

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Table 1: Descriptive Statistics for Analytic Samples								
Treatment group=Took courses online in high school; Comparison group=did not take online courses in high school								
	Full sample		**High school graduates**		**H.S. grad + failed course**		**Dropouts**	
	Treatment	*Comparison*	*Treatment*	*Comparison*	*Treatment*	*Comparison*	*Treatment*	*Comparison*
N	23,911	27,461	9,231	12,725	5,219	3,331	2,951	3,398
Female	0.467	**0.505**	0.510	**0.552**	0.478	**0.508**	0.456	0.401
Black	0.694	**0.572**	0.679	**0.559**	0.689	0.657	0.728	0.627
Asian	0.028	**0.087**	0.036	**0.098**	0.028	**0.058**	0.010	0.044
White	0.077	**0.125**	0.083	**0.146**	0.076	0.084	0.059	0.082
Hispanic	0.193	0.209	0.196	0.192	0.200	0.197	0.198	0.239
Other race	0.008	0.007	0.007	0.005	0.007	0.004	0.005	0.007
English language learner	0.078	**0.112**	0.065	**0.075**	0.064	**0.084**	0.073	0.141
Free lunch	0.817	**0.767**	0.811	**0.738**	0.823	0.837	0.833	0.853
Student with disabilities	0.221	0.219	0.165	**0.142**	0.181	0.173	0.239	0.348
Percent absent	0.247	**0.173**	0.169	**0.089**	0.185	**0.125**	0.382	0.450
GPA	1.487	**2.102**	1.853	**2.488**	1.475	**1.720**	0.872	0.853
Worked before HS exit	0.794	0.792	0.796	0.796	0.796	0.772	0.636	0.586
Spring scaled score† - reading	-0.195	**0.107**	-0.079	**0.246**	-0.108	**-0.057**	-0.578	**0.040**
Spring scaled score† - math	-0.245	**0.144**	-0.129	**0.285**	-0.173	**-0.064**	-0.592	**0.044**
Worked in 2nd year before HS exit	0.700	0.682	0.676	0.668	0.679	0.667	0.596	0.587
Earnings year before HS exit	3532.83	3431.11	3566.63	3456.81	3594.60	**3277.55**	1957.33	1399.22
Earnings 2nd year before HS exit	2140.9	1943.95	1923.69	1821.61	1950.95	1873.49	1304.90	1013.64
Ever took a course online in HS	0.422	**0.578**	0.413	**0.587**	0.607	**0.394**	0.465	0.335
% online users in HS	0.327	**0.305**	0.308	**0.143**	0.278	**0.152**	0.395	0.433
Failed a course in HS	0.789	**0.458**	0.727	**0.355**	n.a.	n.a.	0.874	0.852
Year graduated/exited HS - 2011	n.a.	n.a.	0.000	0.000	0.000	0.000	0.128	0.298
Year graduated/exited HS - 2012	n.a.	n.a.	0.081	0.228	0.026	0.031	0.182	0.205
Year graduated/exited HS - 2013	n.a.	n.a.	0.141	0.183	0.102	0.294	0.229	0.183
Year graduated/exited HS - 2014	n.a.	n.a.	0.162	0.156	0.141	0.217	0.180	0.125

Year graduated/exited HS - 2015	n.a.	n.a.	0.197	0.144	0.233	0.147	0.282	0.188
Year graduated/exited HS - 2016	n.a.	n.a.	0.196	0.150	0.233	0.161	0.000	0.000
Year graduated/exited HS - 2017	n.a.	n.a.	0.224	0.137	0.265	0.149	0.000	0.000

Notes: Coefficient estimates in boldface are statistically significant at α=0.05.
†The reading and math scaled scores are the last (most recent) available for each student and may not be the same time point (e.g., grade level) for each student.

Table 2: Descriptive information on earnings after high school exit by graduates and dropouts					
		High school graduates		**Dropouts**	
Outcome measures		*Treatment*	*Comparison*	*Treatment*	*Comparison*
	N	9,231	12,725	2,951	3,398
Ever enrolled in college after H.S.	*%*	*43.4*	*64.2*	*10.6*	*10.1*
	N	8,047	10,109	1,822	1,417
Percent w/earnings info 1 yr. after H.S.	*%*	*87.2*	*79.4*	*61.7*	*41.7*
Percent w/0 earnings 1 yr. after H.S.	*%*	*6.0*	*11.2*	*22.3*	*28.5*
Earnings yr. 1 after HS exit	$	7307.19	6477.60	3130.46	2531.89
	N	6,275	8,782	2,094	1,753
Percent w/earnings info 2 yrs. after H.S.	*%*	*68.0*	*69.0*	*71.0*	*51.6*
Percent w/0 earnings 2 yrs. after H.S.	*%*	*6.2*	*7.1*	*14.6*	*18.4*
Earnings yr. 2 after HS exit	$	9914.08	9392.43	4721.59	4200.86
	N	4,618	7,221	2,218	1,956
Percent w/earnings info 3 yrs. after H.S.	*%*	*50.0*	*56.7*	*75.2*	*57.6*
Percent w/0 earnings 3 yrs. after H.S.		*6.1*	*6.0*	*12.0*	*15.6*
Earnings yr. 3 after HS exit	$	11797.79	11864.42	5857.78	5360.82
	N	2,994	5,785	1,592	1,588
Percent w/earnings info 4 yrs. after H.S.	*%*	*32.4*	*45.5*	*53.9*	*46.7*
Percent w/0 earnings 4 yrs. after H.S.	*%*	*5.4*	*6.2*	*10.5*	*14.2*
Earnings yr. 4 after HS exit	$	13402.80	13934.52	6980.28	6697.45
	N	1,712	4,164	1,165	1,334
Percent w/earnings info 5 yrs. after H.S.	*%*	*18.5*	*32.7*	*39.5*	*39.3*
Percent w/0 earnings 5 yrs. after H.S.	*%*	*6.5*	*5.8*	*11.2*	*10.3*
Earnings yr. 5 after HS exit	$	14412.83	16471.91	8243.31	8031.14

Table 3: OLS and Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for High school Graduates

Treatment=Took courses online in high school

		High school graduates					
Post-H.S. earnings and employment	N	*OLS*	*IV*	*n*	*Enrolled college - IV*	*n*	*No college - IV*
1 yr. after graduation	8,835	193.37	473.01	4,967	441.68	3,386	-504.55
2 yrs. after graduation	6,005	-34.52	143.57	3,503	-83.52	2,502	-911.31
3 yrs. after graduation	3,473	-233.19	**-1806.24**	2,199	**-3808.76**	1,274	-245.94
4 yrs. after graduation	1,692	-367.71	*-1776.34*	1,114	**-3296.30**	578	*-1913.44*
5 yrs. after graduation	1,674	-705.78	***-2898.21***	1,104	***-6864.07***	570	*1585.46*
		High school graduate + failed course					
Post-H.S. earnings and employment	N	*OLS*	*IV*	*n*	*Enrolled college - IV*	*n*	*No college - IV*
1 yr. after graduation	4,720	111.72	-415.08	2,079	-516.91	2,641	-508.24
2 yrs. after graduation	3,250	44.99	-556.86	1,507	-1117.51	1,743	-541.07
3 yrs. after graduation	1,892	-193.08	-1811.22	981	**-4237.47**	911	-833.13
4 yrs. after graduation	954	-815.59	-2175.58	529	-3416.41	425	-3696.91
5 yrs. after graduation	933	-760.69	-2290.26	516	**-5928.29**	417	*2264.35*

Notes: Coefficient estimates in boldface are statistically significant at α=0.05. The student and school covariates included in the OLS and IV (2SLS) models are shown in Appendix A. Coefficient estimates that are italicized did not satisfy the test of overidentifying restrictions.

Table 4: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for High school Graduates by Gender

	Females			***Males***		
	High school graduates			**High school graduates**		
Post-H.S. earnings and employment	**H.S. grads**	*Enrolled college*	*No college*	**H.S. grads**	*Enrolled college*	*No college*
1 yr. after graduation	n=4,934	n=3,026	n=1,908	n=3,901	n=1,941	n=1,960
	849.72	493.53	2.30	-14.05	308.85	-1011.89
2 yrs. after graduation	n=3,451	n=2,181	n=1,270	n=2,554	n=1,322	n=1,232
	372.17	-20.06	-275.00	*-14.97*	-21.10	-1508.32
3 yrs. after graduation	n=2044	n=1,397	n=647	n=1,429	n=802	n=627
	-1912.78	**-3841.14**	-174.82	-1295.98	-3422.73	-528.21
4 yrs. after graduation	n=1,028	n=735	n=293	n=664	n=379	n=285
	-582.44	-2984.85	154.74	-4008.74	-4942.69	*-3327.59*
5 yrs. after graduation	n=1,008	n=722	n=286	n=666	n=382	n=284
	-2749.22	***-6460.28***	*1760.95*	-4017.28	**-9049.87**	2519.68
	H.S. graduate + failed course			**H.S. graduate + failed course**		
Post-H.S. earnings and employment	**H.S. grad + failed course**	*Enrolled college*	*No college*	**H.S. grad + failed course**	*Enrolled college*	*No college*
1 yr. after graduation	n=2,429	n=1,187	n=1,242	n=2,291	n=892	n=1,399
	27.69	-772.88	366.80	-1040.88	-343.03	-1439.79
2 yrs. after graduation	n=1,722	n=873	n=849	n=1,528	n=634	n=894
	-632.35	-1886.48	*-185.26*	-642.10	-843.67	-548.98
3 yrs. after graduation	n=1,019	n=579	n=440	n=873	n=402	n=471
	-1909.02	**-5100.60**	1874.00	-1805.03	-3434.39	-815.72
4 yrs. after graduation	n=513	**n=316**	n=197	n=441	n=213	n=228
	-1397.62	-3743.74	351.37	-3793.90	-5414.80	*-2919.00*
5 yrs. after graduation	n=498	n=306	n=192	n=435	n=210	n=225
	-107.83	*-3656.11*	3931.91	**-6163.39**	***-10956.19***	255.21

Notes: Coefficient estimates in boldface are statistically significant at α=0.05. The student and school covariates included in the IV (2SLS) models are shown in Appendix A. Coefficient estimates that are italicized did not satisfy the test of overidentifying restrictions.

Table 5: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings				
Adjusting for missing data				
	High school graduates			**Dropouts**
Post-H.S. earnings and employment	All H.S. grads (n=11,941)	*Enrolled college (n=6,365)*	*No college (n=5,576)*	*Dropouts (n=968)*
1 yr. after graduation	127.02	158.28	*-462.20*	*-824.33*
2 yrs. after graduation	*108.85*	*215.78*	-468.27	-490.95
3 yrs. after graduation	***-446.73***	***-766.57***	-348.13	*-1298.47*
4 yrs. after graduation	*-177.31*	-427.59	-135.94	-1755.91
5 yrs. after graduation	*80.37*	*-580.17*	*693.61*	**-1920.63**
	H.S. graduate or dropout + failed course			
Post-H.S. earnings and employment	All H.S. grad + failed course (n=6,422)	*Enrolled college (n=2,602)*	*No college (n=3,810)*	*Dropouts (n=863)*
1 yr. after graduation	-345.09	-456.70	-358.74	*-844.07*
2 yrs. after graduation	-316.31	-450.78	-383.48	-1019.42
3 yrs. after graduation	**-723.92**	**-1562.01**	-119.03	***-2682.11***
4 yrs. after graduation	-224.63	-567.60	-98.90	*-1890.21*
5 yrs. after graduation	163.88	*-838.01*	*808.34*	-1822.14

Notes: Coefficient estimates in boldface are statistically significant at α=0.05.
The student and school covariates included in the OLS and IV (2SLS) models are shown in Appendix A.
Coefficient estimates that are italicized did not satisfy the test of overidentifying restrictions.

Figure 1a: Descriptive Trends of Student Quarterly Earnings Prior to High school Graduation, by Online Course-taking in High School

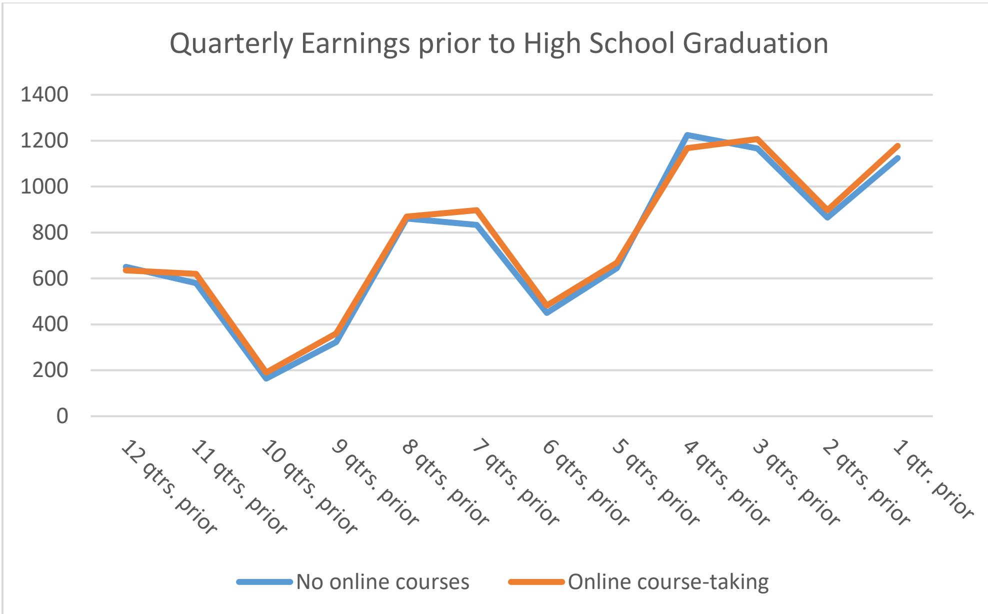


Figure 1b: Descriptive Trends of Student Quarterly Earnings Prior to High School Exit, by Online Course-taking in High School

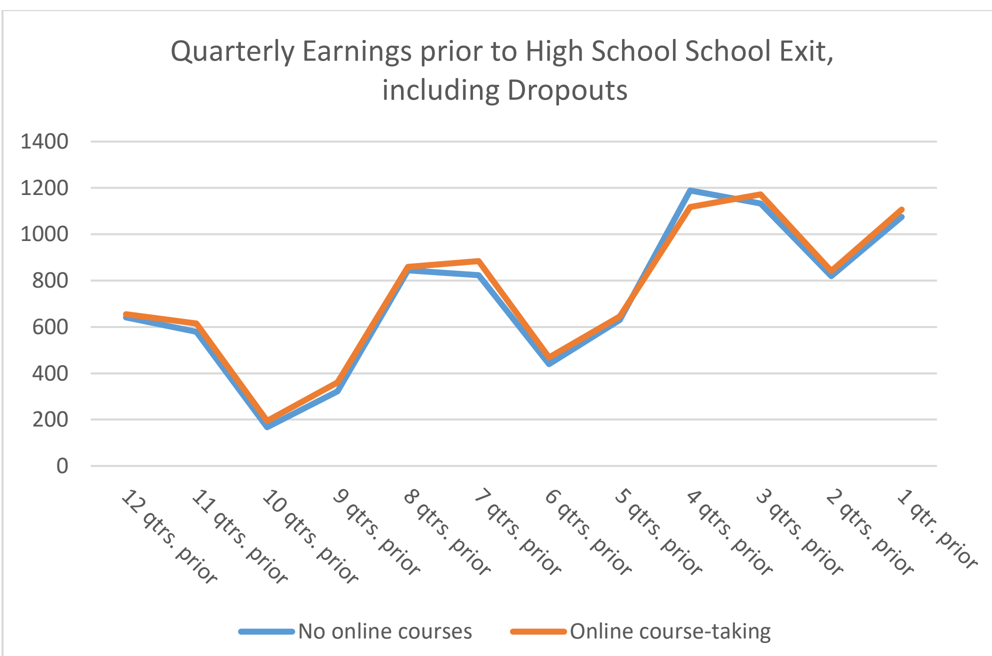


Figure 2a: Descriptive Trends of Student Annual Earnings Before and After High School Graduation, by Online Course-taking

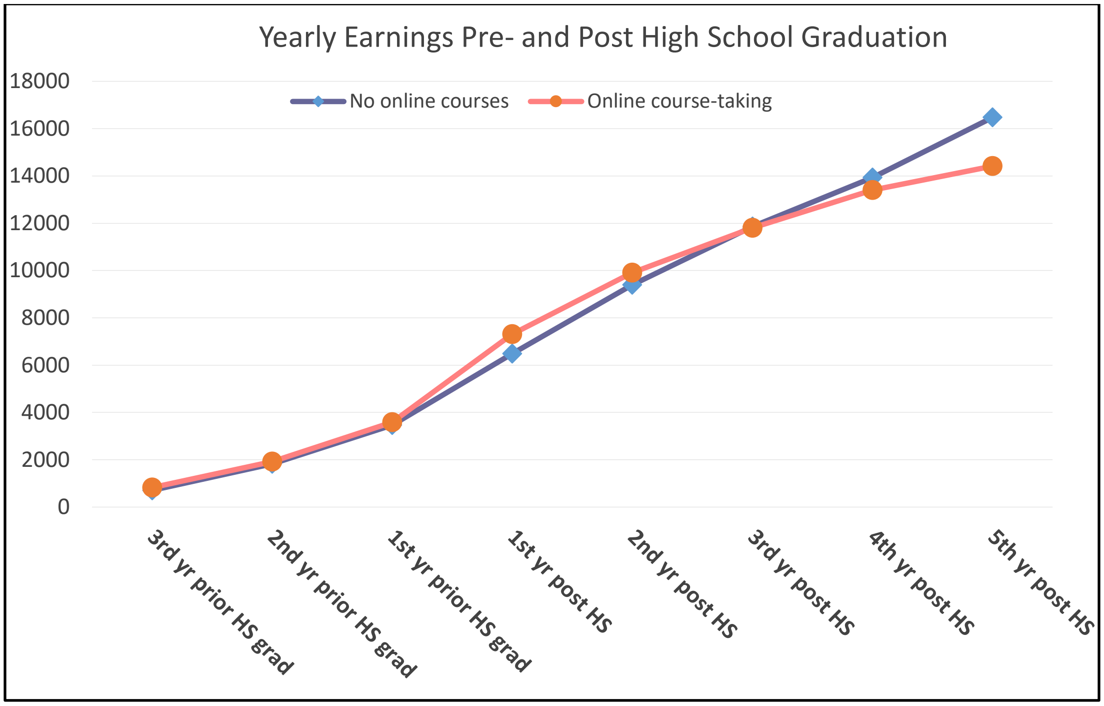


Figure 2b: Descriptive Trends of Student Annual Earnings Before and After High school Graduation, by Online Course-taking, Comparing HS Graduates and Graduates Who Failed a Course in High School

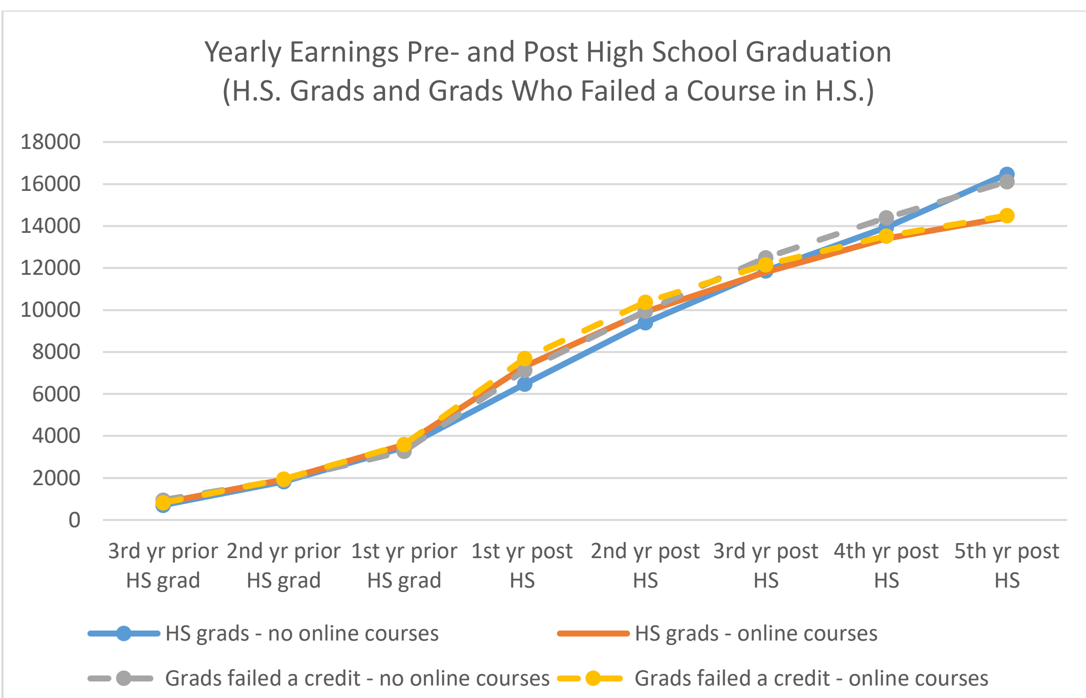


Figure 3: Descriptive Trends of Student Annual Earnings by Online Course-taking Before and After High School Exit for High School Dropouts

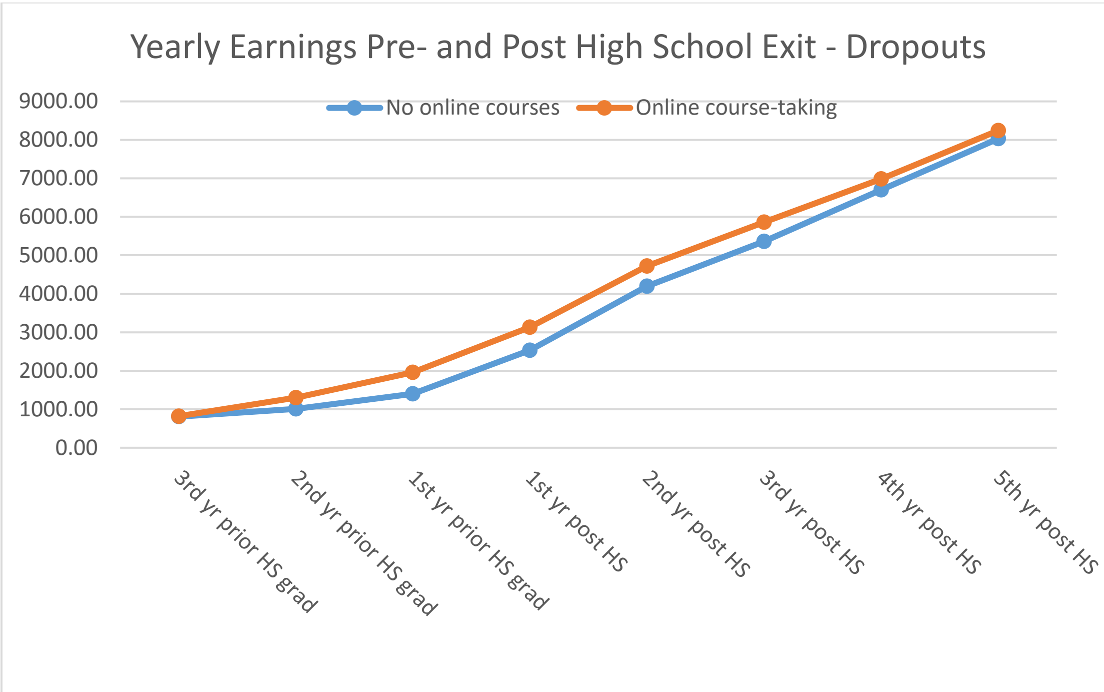
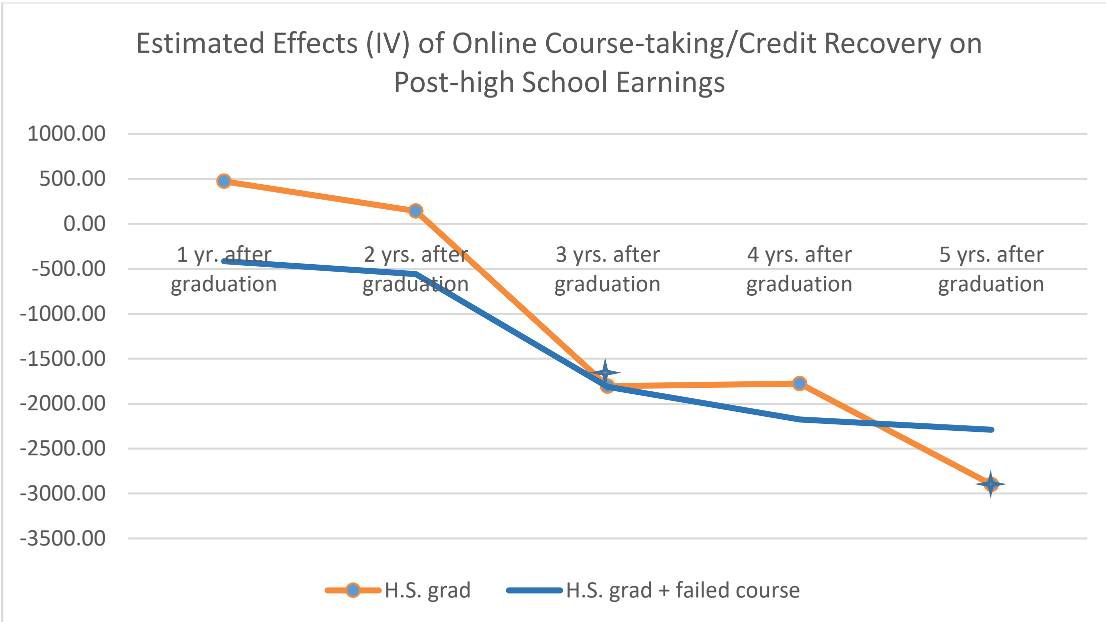
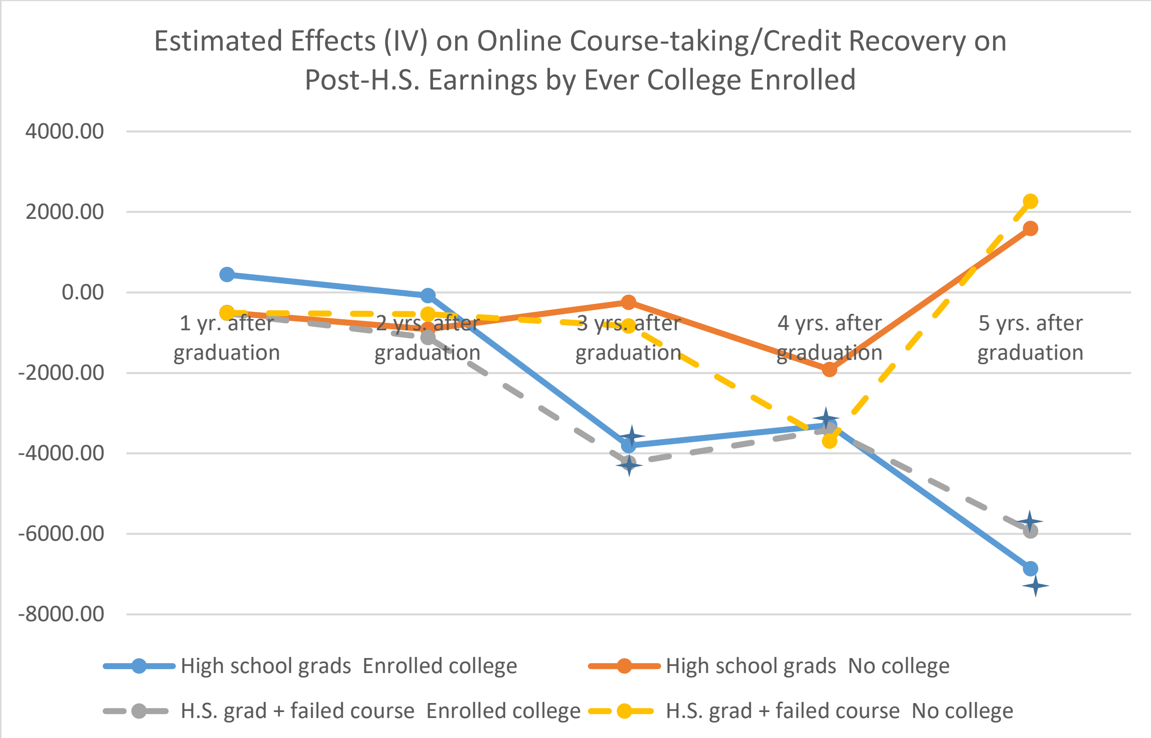


Figure 4: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates



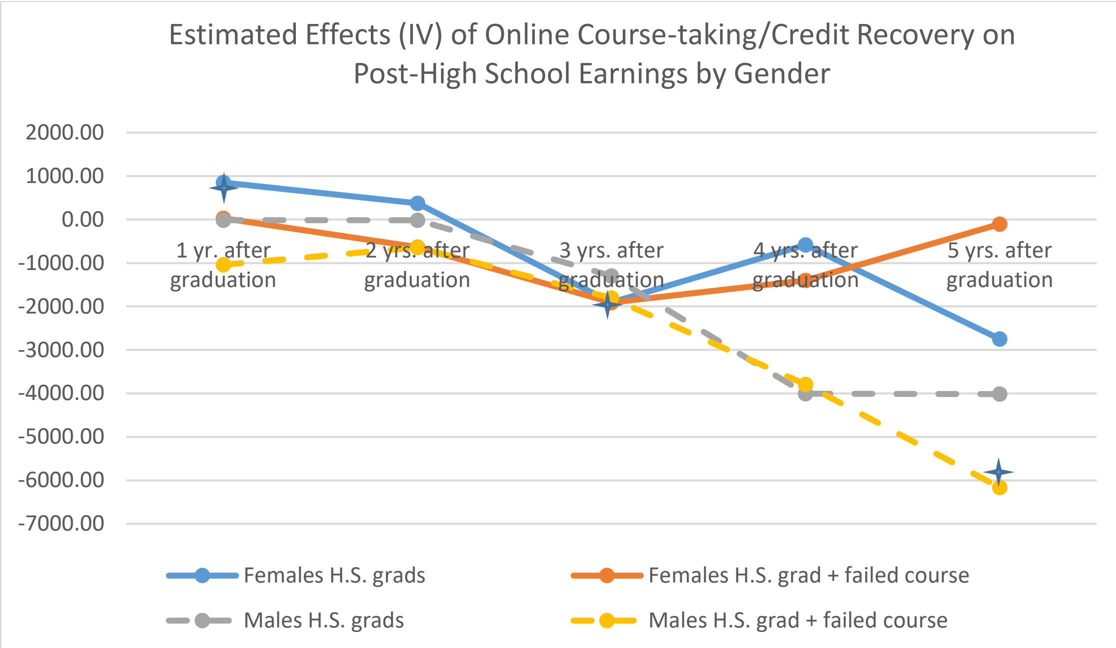
See Table 3 for a tabular summary of these results and notes on the estimation. The symbol, ✦, indicates a statistically significant coefficient estimate.

Figure 5: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates by College Enrollment



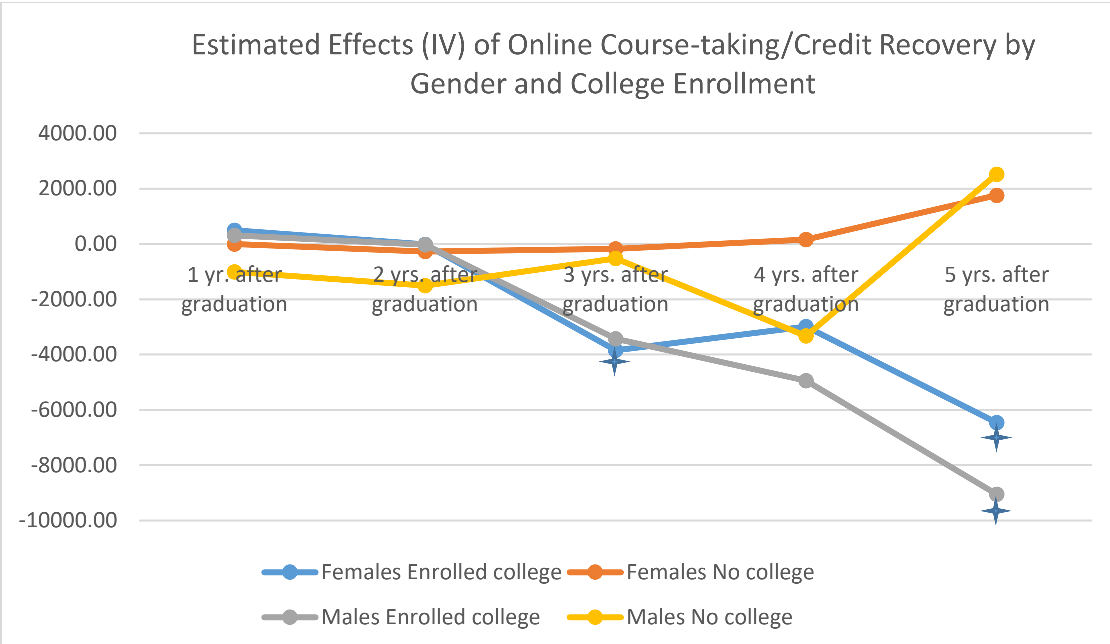
See Table 3 for a tabular summary of these results and notes on the estimation. The symbol, ✦, indicates a statistically significant coefficient estimate.

Figure 6: Instrumental Variables Regression Estimates by Gender of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates



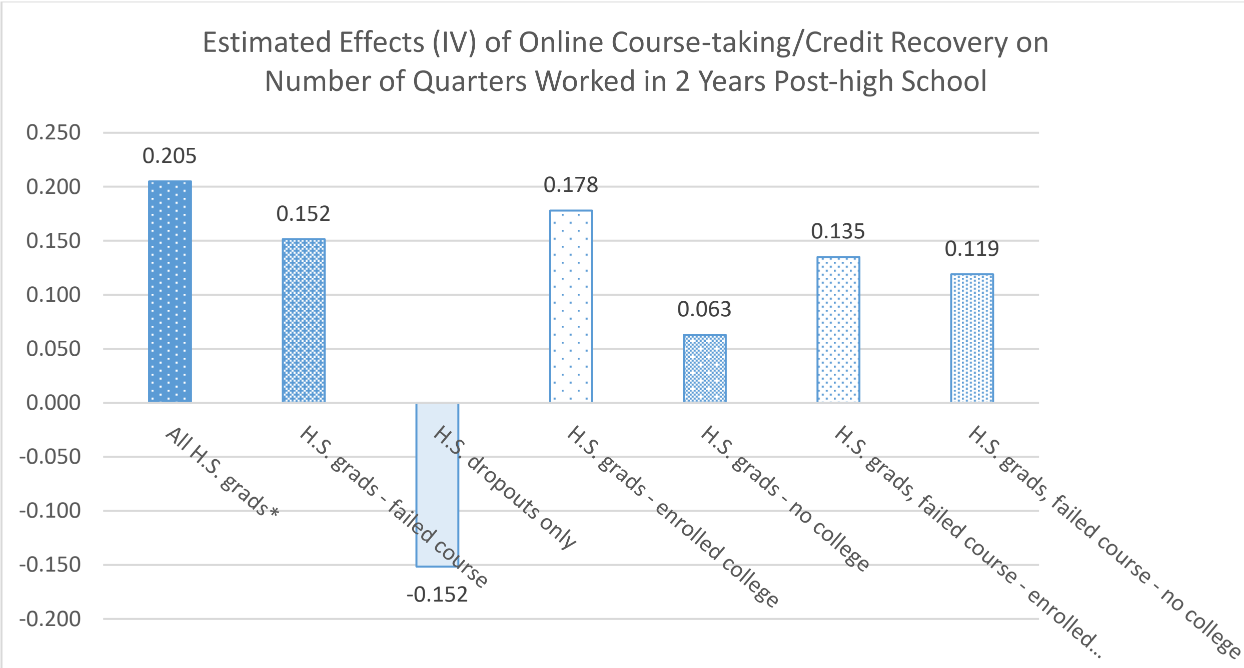
See Table 4 for a tabular summary of these results and notes on the estimation. The symbol, ✦, indicates a statistically significant coefficient estimate.

Figure 7: Instrumental Variables Regression Estimates by Gender of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates by College Enrollment



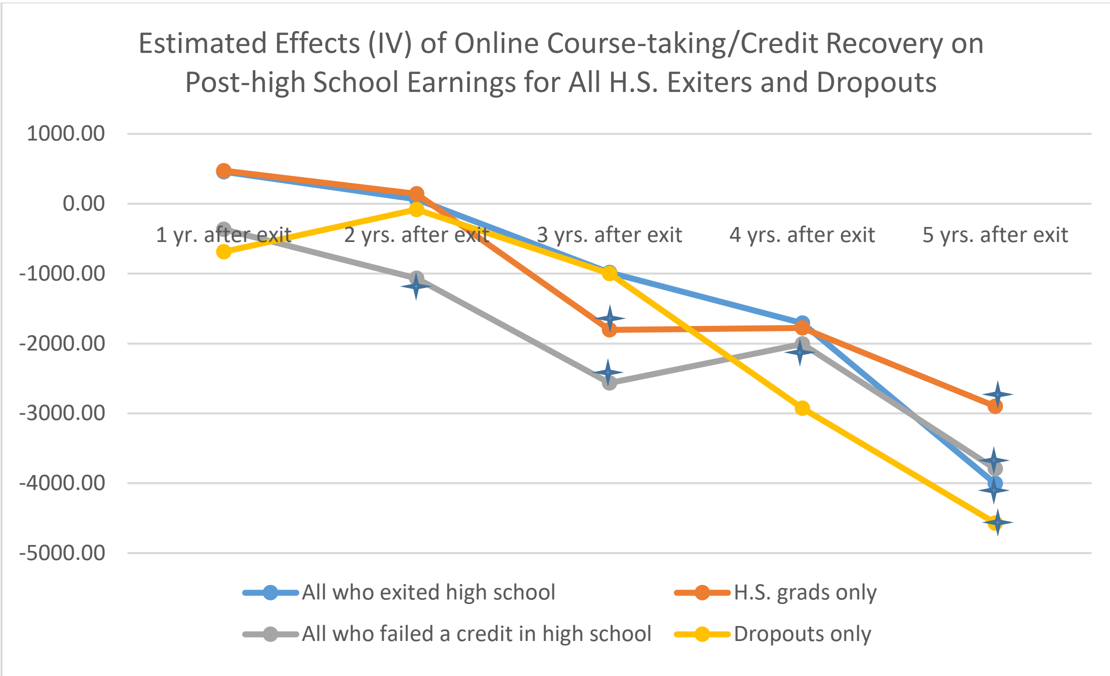
See Table 4 for a tabular summary of these results and notes on the estimation. The symbol, ✦, indicates a statistically significant coefficient estimate.

Figure 8: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Employment for High School Graduates and Dropouts



Note: The student and school covariates included in the IV (2SLS) models are shown in Appendix A. * on a category label indicates statistically significant estimate effect at α=0.05.

Figure 9: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for Dropouts (Compared to Effects for All H.S. Exiters)



Appendix A: First-stage Instrumental Variables Model Results

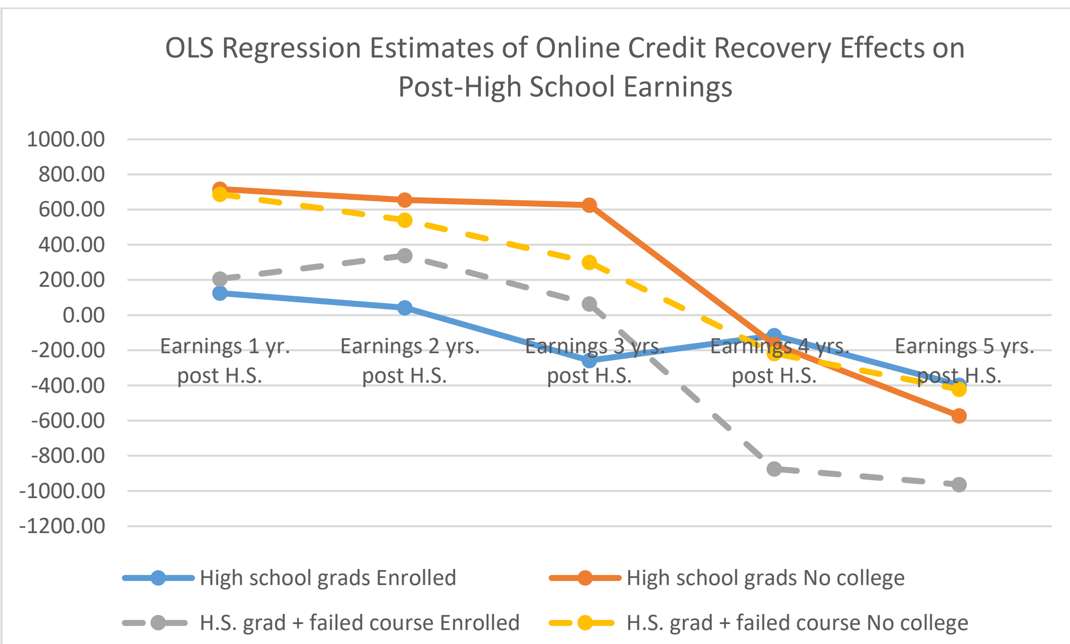
First-stage (IV) model: Predicting participation in online course-taking							
Student characteristics	**High school graduates**				**H.S. graduates - failed a course**		
Female	-0.005	0.009	0.557		-0.012	0.013	0.355
Asian	-0.020	0.018	0.272		-0.065	0.038	0.091
White	**-0.048**	0.014	0.001		**-0.061**	0.024	0.011
Hispanic	**-0.050**	0.013	0.000		**-0.054**	0.020	0.007
Other race	0.010	0.045	0.821		0.008	0.054	0.885
Eng. lang. learner	-0.032	0.022	0.148		-0.026	0.033	0.429
Free lunch	-0.018	0.011	0.088		**-0.046**	0.017	0.006
Student w/disabilities	0.005	0.013	0.693		-0.001	0.018	0.944
Percent absent	**0.321**	0.044	0.000		**0.210**	0.051	0.000
GPA	**-0.111**	0.008	0.000		**-0.141**	0.011	0.000
Earnings yr. before HS exit (in 1,000s)	0.00093	0.00123	0.451		0.00162	0.00169	0.340
Worked before HS exit	0.001	0.012	0.909		-0.005	0.017	0.750
Failed a course in HS	**0.114**	0.013	0.000			(omitted)	
Year graduated - 2012	**-0.326**	0.046	0.000		**-0.340**	0.050	0.000
Year graduated - 2013	**-0.204**	0.012	0.000		**-0.269**	0.019	0.000
Year graduated - 2014	**-0.075**	0.012	0.000		**-0.089**	0.019	0.000
Year graduated - 2015	**0.037**	0.011	0.001		**0.054**	0.016	0.001
School characteristics							
% in online courses	**1.152**	0.032	0.000		**1.228**	0.048	0.000
% Black	**-0.154**	0.029	0.000		**-0.340**	0.042	0.000
% English learners	-0.039	0.092	0.674		**-0.328**	0.119	0.006
% Free lunch	**0.301**	0.078	0.000		**0.647**	0.118	0.000
% Special needs	**0.596**	0.136	0.000		**0.533**	0.184	0.004
% in advanced courses	**-0.099**	0.021	0.000		0.005	0.034	0.881
% in work-based learning	0.185	0.158	0.242		-0.242	0.193	0.209
% in service learning	**-0.227**	0.070	0.001		-0.241	0.094	0.010
% in CTE	**-0.125**	0.015	0.000		**-0.100**	0.020	0.000
Alternative school	**-0.126**	0.027	0.000		**-0.166**	0.033	0.000
Charter school	**-0.128**	0.030	0.000		**-0.322**	0.046	0.000
Citywide specialty school	**0.094**	0.015	0.000		**0.090**	0.019	0.000
Constant	**0.262**	0.068	0.000		0.293	0.102	0.004
Adjusted R-squared	41.68%				32.24%		
Model F value	392				134		

Notes: Coefficient estimates in boldface are statistically significant at α=0.05. Sample sizes from estimation are N=8,835 and N=4,720 (restricted to students who failed a course in high school).

Appendix B: OLS Estimates of Online Course-taking by College Enrollment

OLS Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings					
Treatment=Took courses online in high school					
		High school grads		H.S. grad + failed course	
Post-H.S. earnings and employment		*Enrolled*	*No college*	*Enrolled*	*No college*
Earnings 1 yr. post H.S.	8,835	125.40	**717.10**	206.24	**687.97**
Earnings 2 yrs. post H.S.	6,005	41.57	654.64	338.50	540.46
Earnings 3 yrs. post H.S.	3,473	-258.37	625.97	63.96	299.81
Earnings 4 yrs. post H.S.	1,692	-116.09	-167.45	-874.94	-217.98
Earnings 5 yrs. post H.S.	1,674	-397.51	-572.67	-963	-422.13

Notes: Coefficient estimates in boldface are statistically significant at α=0.05. The student and school covariates included in the OLS and IV (2SLS) models are shown in Appendix A.



Appendix C

Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for All Who Exited High School and H.S. Dropouts						
Post-H.S. earnings	*All who exited high school*	*Failed a credit in high school*	*Dropouts only*	*Dropouts who failed a credit in H.S.*	*Female dropouts - failed a credit*	*Male dropouts - failed a credit*
	n=12,708	n=7,170	n=929	n=830	n=358	n=472
1 yr. after H.S. exit	458.03	-367.47	-689.53	-821.23	***-2044.54***	384.06
	n=9,494	n=5,422	n=883	n=794	n=357	n=437
2 yrs. after H.S. exit	65.74	***-1069.16***	-81.57	-698.51	-1152.84	-495.38
	n=6,775	n=3,971	n=863	n=775	n=345	n=430
3 yrs. after H.S. exit	-986.90	**-2565.01**	-1000.92	***-2711.17***	***-5117.46***	-795.79
	n=4,004	n=2,355	n=527	n=465	n=191	n=274
4 yrs. after H.S. exit	-1710.02	***-2007.26***	-2925.83	-2639.28	-2228.10	-3143.51
	n=2,006	n=1,223	n=332	n=290	n=118	n=172
5 yrs. after H.S. exit	***-4005.24***	***-3794.5***	***-4569.59***	-4616.73	-1811.26	-3223.59
	Females			*Males*		
Post-H.S. earnings	*All who exited high school*	*Failed a credit in high school*	*Dropouts only*	*All who exited high school*	*Failed a credit in high school*	*Dropouts only*
	n=6,930	n=3,574	n=408	n=5,778	n=3,596	n=521
1 yr. after H.S. exit	*581.70*	-352.95	***-2326.31***	222.88	-623.83	449.49
	n=5,257	n=2,751	n=404	n=4,237	n=2,671	n=479
2 yrs. after H.S. exit	-153.86	-934.09	-560.68	254.20	-1528.31	233.71
	n=3,820	n=2,047	n=392	n=2,955	n=1,924	n=471
3 yrs. after H.S. exit	-986.35	***-2592.51***	-2844.93	-1029.38	***-2847.33***	356.05
	n=2,273	n=1,210	n=221	n=1,731	n=1,145	n=306
4 yrs. after H.S. exit	-1655.18	***-2445.45***	-3103.73	-1983.04	-2147.83	***-4581.15***
	n=1,147	n=616	n=139	n=859	n=607	n=193
5 yrs. after H.S. exit	***-3562.235***	-1891.16	-4238.65	***-5209.03***	***-6637.68***	-4870.78
Note: coefficient estimates in boldface are statistically significant at α=0.05; italics indicate that a test of overidentification or for exogeneity of the instrument rejected the null.						

Endnotes

[1] Campbell (1979): "The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor."

[2] https://www.childtrends.org/indicators/youth-employment, accessed Aug. 18, 2019.

[3] Federal law constrains work hours of 14-15 year olds, but students age 16 and older can work unlimited hours.

[4] Altonji's findings were not sensitive to alternative measures of the IV, such as using counts of courses taken rather than courses weighted by hours per week. He also reported that the quantity and quality of courses were positively correlated, and both were correlated as well with more advantaged student and school characteristics.

[5] Student transcripts in the study school district did not distinguish between a course grade earned through credit recovery vs. in a traditional classroom setting.

[6] We empirically examine these relationships again with the analytic sample used in this study.

[7] http://collegeaffordability.urban.org/covering-expenses/working-during-college/#/federal_work_study.

[8] The subsample of data with matched student record-technology vendor data is representative of all students taking courses online in this school district.

[9] We also performed a set of analyses that further restricted the sample of students to those with eighth grade data available to use as the baseline year for treatment (online course-taking). This acknowledges the potential for inflated estimates due to regression to the mean, although it also significantly reduced the sample size to a highly selective (disadvantaged) group of students. These results are available from the authors upon request.

[10] Instrumental variables, matching and OLS regression estimates of the effects of online course-taking for credit recovery on high school completion were inconsistent, and statistical tests suggested that the highly selective differences between high school completers and dropouts could not be fully accounted for in the estimation. Thus, we do not present these results in the paper but can make them available upon request.

[11] If it is overidentified, a statistically significant test statistic will indicate that either the instruments are correlated with the error term (i.e., the instrument is invalid) or the structural equation is incorrectly specified.

[12] Although approximately 10 percent of high school dropouts were recorded to have enrolled in college after exiting high school, as their numbers were comparatively few, we did not include them in the models estimated separately by college enrollment.