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

Carolyn J. Heinrich
Huiping Cheng

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 students who engaged in online credit recovery into the labor market to understand the longer-term implications of this growing educational trend. If online credit recovery contributes to high school completion and facilitates job entry, then participants in online credit recovery may have labor market outcomes that differ little relative to those recovering credits in traditional classroom settings. 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 credit recovery participants may earn less over time. The study findings suggest that high school students who participated in online credit recovery initially had earnings on par with those who did not recover course credits online, but a negative differential emerged between their earnings and the earnings of nonparticipants that grew over time. We found no evidence to suggest that students ever benefitted in the labor market from online credit recovery in high school.

INTRODUCTION

The high school graduation rate, as Heckman and LaFontaine (2010, p. 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 (Heckman & LaFontaine, 2010; Murnane, 2013).[1] Concerns about the accuracy of graduation rate measures were elevated when the No Child Left Behind (NCLB) Act of 2001 made them a key

[1] For example, estimates of returns to a high school degree 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.

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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 2010/2011 school year.

The trend in U.S. graduation rates turned positive after 2000, increasing an estimated six percentage points between 2000 and 2010; in addition, achievement (test score) gains were larger among low-income students and those of color (Dee & 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, Herzog, & MacIver, 2007; Dee & 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 2010/2011 and 2016/2017 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.

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.[2] Dynarski and others (Hansen, 2017; Harris et al., 2020; Malkus, 2018; Morgan, Sinatra, & Eschenauer, 2015) 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), "shortcuts" that provide alternate, easier options to complete a high school degree, or "fudging" the numbers (e.g., removing students from graduation cohorts).

This study focuses on one of these alternative options, offered through digital instructional programs and commonly known as "online credit recovery," in which high school students repeat failed courses in an alternative (online) and sometimes abbreviated format. An emerging body of research links online 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 & Darling-Aduana, 2021; Viano, 2018; Viano & Henry, 2019). This study follows high school students who failed at least one course in high school and engaged in online instruction to recover those credits (instead of repeating the course in a traditional classroom) into the labor market to understand the longer-term implications of this growing educational trend for their employment and earnings. If, as some research suggests (Levin, 2009), high school completion improves

[2] 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."

noncognitive outcomes among students in ways that enhance their labor market prospects (independent of academic performance), making the attainment of a high school diploma less costly through credit recovery could potentially improve these students' labor market outcomes. However, if high school courses and degree completion through online credit recovery are inferior to traditional classroom instruction in terms of students' cognitive and noncognitive skills development, this could potentially devalue the high school credential in the labor market, to the further detriment of students directed to online 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. Especially for students heading directly to the labor market, 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. Yet concerns about high schoolers working outside of school, pertaining to the potential loss of hours for study time, increased absenteeism, and poorer school performance, might be only partially alleviated by online course-taking options (Quirk, Keith, & Quirk, 2001; Rothstein, 2007; Tyler, 2003). 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 and effects 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 for credit recovery in 2010, and by the 2017/2018 school year, about half of students exiting high school had completed at least one course through the online course-taking system. Data from student school records were linked to data from the technology (online instructional program) vendor to construct detailed, student-level measures of online and traditional course-taking in high school from 2010/2011 to 2017/2018. 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 methodology employed in the analysis. We limit the analytical sample to high school students who failed at least one course in high school and would have had options for online credit recovery or repeating the course in a traditional face-to-face classroom setting, given the timing of the school district's adoption of online credit recovery.

The findings of our instrumental variables estimation suggest that high school exiters who engaged in online credit recovery initially had earnings on par with those who did not repeat courses online. Over time, however, a large negative differential emerged between their earnings and those of students who did not repeat courses online in high school. At the same time, there were no statistically significant differences in the likelihood of being employed or the likelihood of retaining employment for online credit recovery participants compared to nonparticipants in the four post-high school years. This suggests that the increasingly negative differential in estimated earnings for online credit recovery participants may have been more likely driven by lower wages received on the job (or a slower rate of increase in earnings compared to nonparticipants) than by their employment rates. The findings are consistent with human capital theory and the inference that ability is gradually revealed over time in the labor market. We found no evidence to suggest that students ever benefitted in the labor market from online credit recovery in high school.

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. Failing courses in high school sets students behind in their progress toward graduation, and it is also costly for schools when students have to repeat (and pass) core courses or other credits that are required to graduate. Heinrich and Darling-Aduana (2021) estimated that online credit recovery program costs per student are approximately 50 percent of the cost of providing credit recovery in a traditional classroom setting. Particularly for large, urban high school districts with greater numbers of students failing courses and 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 to 20 percentage points (Heinrich & Darling-Aduana, 2021; Kirsch, 2017; Malkus, 2018).

Although some 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 (Heinrich et al., 2019; Heppen et al., 2017; Viano, 2018; Viano & Henry, 2019). Research that has looked into how students engage with online credit recovery programs likewise questions whether students directed to repeat their high school courses online are learning in those courses. As part of a larger research study, we conducted hundreds of classroom observations of credit recovery, as well as some observations of traditional (face-to-face) credit recovery classrooms (Heinrich et al., 2019). The online credit recovery 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, limited teacher expertise with the course content, and low teacher expectations for student learning (Heinrich et al., 2019). In traditional credit recovery classrooms, we observed comparatively lower student-teacher ratios, more teacher-student interactions to support instruction, and content-based grouping of students. In an experimental study that compared freshman who took Algebra 1 through an online program vs. face-to-face instruction, Rickles et al. (2018) reported that although students were allowed to move at their own pace through online instruction, they were lacking in supports to help those struggling with the content, and the "mentors" or aides were not expected to be certified mathematics teachers or to provide instructional support. In fact, the International Association for K-12 Online Learning that develops national standards and builds communities of practice for online instruction critiqued online credit recovery as "low-cost" programs that have "very low levels (if any) of teacher involvement and require very little of students in demonstrating proficiency. They are used primarily because they are inexpensive, and they allow schools to say students have ‘passed’ whether they have learned anything or not” (Powell, Roberts, & Patrick, 2015, p. 10).

HUMAN CAPITAL EXPLANATIONS AND EVIDENCE

Online credit recovery is germane to 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. 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, students completing their high school courses with the aid of online credit recovery programs could face poorer labor market prospects. In their study of high school students in Texas and Florida, Clark and Martorell (2014) compared those who barely passed and barely failed high school exit exams to assess the signaling value of a high school degree. They found considerable variation in earnings among school completers that was correlated with diploma status, which they surmised was based on firms’ ability to acquire information on applicants’ productivity. They thus concluded that the returns to a high school diploma were likely reflecting productivity differences (rather than signaling value). 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 (Altonji, 1995; Kang & Bishop, 1986).

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 to 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 school 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).[3] 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 percent), less than the value of a year in high school, with no subsequent improvement in wages over the 13 years following the students’ high school graduation.

Although decades have passed and curricula has changed since Altonji’s (1995) analysis, his findings have particularly important bearing on the investigation of online 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

[3] 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.

that as long as students persevere through another year of high school, making attainment of a high school 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. More recently, Gottfried and Plasman (2018) applied a similar IV estimation strategy to Altonji and found that high school career and technical education (CTE) course-taking increased the probability of on-time graduation from high school. In addition, Goodman (2019) studied state changes in high school minimum math requirements and found strong evidence that increases in completed math coursework were linked to increased adult earnings, particularly for Black students whose course-taking was affected by the reforms.

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 are not directly determined by them. Employers are limited in the attributes they directly observe about a prospective worker's productivity; for example, whether students completed a course credit through online credit recovery (after failing a course) is not observable on their high school transcript (nor is the initial course failure). Employers may thus use an individual's education level (e.g., receipt of a high school diploma) to make inferences about characteristics they are not able to observe but that 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.

Arcidiacono, Bayer, and Hizmo (2010) explored related questions about sorting and signaling using data from the National Longitudinal Survey of Youth, which includes standardized measures (the Armed Forces Qualifying Test, AFQT) that can proxy for ability. They compared the extent to which the wages of high school graduates vs. college graduates were related to their ability, assuming that education at the college level more directly conveys ability to the labor market via explicit information such as college attended, GPA, majors, etc. Their analysis confirmed that while ability is accurately observed for college graduates, it is revealed more gradually for high school completers in the labor market. In other words, the signaling value of a high school diploma will wane as firms gain more knowledge about worker productivity, and as Altonji and Pierrett (2001) concluded in their earlier study, pay will become more tied to productivity and less dependent on any easily observable characteristics or credentials.

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, Levin (2012) points out that 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 et al., 2001; Murnane, Willett, & 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 they exit high school (with or without a high school degree).

It is also possible that by making the attainment of the diploma less arduous through online credit recovery (i.e., less time and effort), more students would be motivated to complete a high school degree. The online credit recovery program examined in this study allows students to take online course pretests and potentially "test out of" or bypass some or all parts of online course instruction, thereby allowing them to complete courses in fewer sessions. Heinrich and Darling-Aduana (2021) found positive associations between use of this online credit recovery program and high school graduation, ranging from about 5 to 13 percentage points (depending in part on the intensity of online course-taking). 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 noncognitive 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.

RESEARCH HYPOTHESES

The theories and research evidence discussed above suggest a potential concern that high school courses recovered online may not impart the same level of skills or human capital as courses repeated in face-to-face instruction, although they may help high school students to recover credits more quickly and stay on track for timely completion. Because high school transcripts do not reveal if a course was failed and then repeated online to attain credit, employers would not necessarily suspect any skills deficits associated with online credit recovery at the time of hire. Accordingly, we would not expect differences in *immediate* post-high school earnings based on the mode of credit recovery for students who failed courses in high school, conforming to the expectations set out by signaling or sorting theories. That said, human capital theory predicts that if high school online credit recovery courses are inferior in terms of the learning that takes place and that learning is critical to workplace productivity, online credit recovery participants may earn less in the labor market over time, if in later post-high school quarters or years employers observe that these students perform relatively more poorly on the job. In addition, online credit recovery program participants might work fewer quarters following their exit from high school if they are less likely to retain jobs over time.

STUDY TREATMENT, DATA, SAMPLES, METHODS, AND MEASURES

In the large urban school district that is the site of this study, course failure rates across high schools in the district are relatively high. At the 5th percentile of high schools in the district, about one-third of high school students have failed a course, where the average is about two-thirds, and the median is 71 percent (of students in high school failing at least one course) during our study period. This translates into a very high cost for the school district in providing opportunities (seats in classrooms) for credit recovery.

In this study, the treatment of interest—online course-taking for credit recovery—takes place during the students' high school years. To enable high school students to repeat courses necessary for graduation, the school district provides credit-recovery course options in traditional classroom settings as well as online. The school district purchased a license from an online credit recovery program vendor that allows a specified number of students to be logged into the system at any given time (inside or outside of school). In the first year (2010/2011) the online credit recovery program was adopted, approximately 5 percent of high school students took at least one course online, and this rose to more than 40 percent of high school students over the study period. It took time for schools to determine the physical, technological, and personnel infrastructure necessary to operate the online course-taking system and manage student use effectively, but most schools eventually offered online credit recovery. Less than 3 percent of students attended high schools over the study period that did not provide online credit recovery opportunities, and of the high school students who accessed the online course-taking system, nearly four-fifths had failed a course.

During this period of ramping up online credit recovery, the proportion of students taking courses online varied considerably both between and within the districts' 46 high schools (e.g., from zero to more than 93 percent). Interviews with district staff and teachers suggested that school-level administrative and staffing decisions were among the most important factors determining the incidence of online credit recovery (Heinrich & Darling-Aduana, 2021). For example, in one school, a new school principal wanted to learn more about the online course-taking system before committing instructional space for its use, and hence in her first year, only students who had not completed online courses initiated in the prior year were allowed to continue (contributing to a steep decline in the rate of student online course-taking that year). The district credit recovery program coordinator explained that when administrative and instructional considerations (e.g., regarding space, staffing, programming, and other resources) allowed it, both schools and students preferred the online option for credit recovery. It was more costly for schools to place students in traditional classrooms to repeat a course, and very few students preferred the semester-long, traditional classroom route, because they could test out of course modules and work at a faster pace to complete courses in online credit recovery (Heinrich et al., 2019). Among the students who failed a course over our study period, 57 percent repeated the courses through online credit recovery, completing, on average, about two courses through online credit recovery, although the number of courses taken online ranged as high as more than 16 for a given student. While initially the district allowed online course-taking (not for credit recovery) among ninth graders, this practice was swiftly discontinued because they were not effective users of the system (Heinrich et al., 2019).

Study Data

The school district provided school records for all high school students from the 2010/2011 through 2017/2018 school years. These include student demographic information, absences and suspensions, course credits earned, grade point average (GPA), ACT scores, and standardized test scores; we also received data from the state department of education that identified high school dropouts. 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.[4] 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 study school district is among the top 50 school districts in the U.S. (by population size). 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 after their exit from high school to student school records. Measures of students' employment and earnings are available for seven cohorts of students who attended high school in the study district after it rolled out the online credit recovery program. Matches between the student records and UI data were identified for 98.8 percent of these high school students. For each student, there are as many as four years of earnings records before high school exit and up to seven years (30 quarters) of post-high school earnings data, varying according to the years in which the students entered high school. The UI records include total earnings per quarter, employment by quarter, and employers the student worked for in a given quarter. As expected, for the earlier cohorts of students, there are more quarters of post-high school employment and earnings available than for later cohorts. In addition, because of labor restrictions on children under age 16, few students work in their first two years of high school.

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 they worked for in reference to the students' *expected* (on-time) quarter and year of exit from high school, which were defined based on the quarter and year they first enrolled in high school. For example, for a student first entering high school in fall 2010, 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. We also constructed measures of the number of consecutive quarters that each individual had earnings after their expected exit from high school, and the number of consecutive quarters that they worked for the same employer to assess post-high school employment retention.

Study Samples and Descriptive Information

We began with a study sample frame including all high school students in the district who were enrolled sometime in the 2010/2011 through 2017/2018 school years and subsequently exited high school. Given that the treatment of interest is participation in online credit recovery, we restricted our primary analytic sample to students who failed at least one course in high school. Of course, students leaving high school in more recent years will have comparatively fewer quarters of post-high school exit earnings information. In addition to the timing of exit, missing data on the outcome variables (quarterly or annual earnings and employment) could also occur for any

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

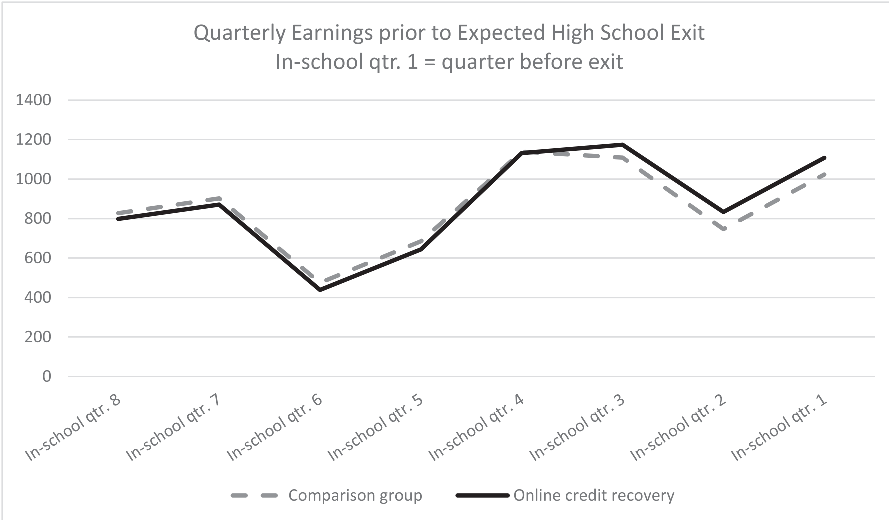


Figure 1. Descriptive Trends in Student Quarterly Earnings Prior to Expected High School Exit by Online Credit Recovery Participation in High School.

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. We therefore also performed our analyses on a (constant) subsample who had earnings records for four full years (16 quarters) following their expected exit from high school. Basic descriptive information on student and school characteristics for the sample frame, students who failed a course in high school, and the subsample of students with four full years of post-high school earnings records is presented in Table 1 (separately for students who engaged in online credit recovery and those who did not).

The descriptive statistics presented in the first two columns of Table 1 show that there are statistically significant differences (indicated in boldface) between students engaging in online credit recovery (the treatment group) and the comparison group that did not participate in online credit recovery across student demographic and school characteristics (confirmed in two-sample tests). Black students were more likely to engage in online credit recovery, as were students who were absent more frequently, had lower grade point averages (GPAs), and were earning fewer credits. White and Asian students, English language learners, and those with disabilities were less likely to recover failed credits online. 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 earnings while in high school, there were no statistically significant differences in students' earnings in the years before they exited high school by whether they took courses online for credit recovery. In fact, Figure 1 shows parallel trends in *quarterly* earnings across eight quarters before expected high school exit between online credit recovery participants and those who did not repeat courses online. Looking at *school* characteristics in Table 1, students participating in online credit recovery attended schools in which higher proportions of other students were taking courses online, were free or reduced-price lunch eligible, and had disabilities, and they were more likely to be attending alternative high schools and schools with higher average student mobility and were less likely to attend charter schools (relative to neighborhood schools). Online credit recovery participants also attended high schools where

Table 1. Descriptive statistics for study samples and all students exiting high school during the study period.

Treatment group = took courses online in H.S.; Comparison group = no online courses in H.S.	Students who failed at least one course in H.S.				Students who failed a course and had four years of post-H.S. UI earnings information				All high school exiters			
	n	*Treatment*	*n*	*Comparison*	*n*	*Treatment*	*n*	*Comparison*	*n*	*Treatment*	*n*	*Comparison*
Student characteristics												
Female	6,344	0.472	4,534	0.480	1,615	0.501	1,654	0.512	11,141	**0.498**	14,905	0.530
Black	6,344	**0.693**	4,534	0.648	1,615	**0.723**	1,654	0.655	11,141	**0.687**	14,905	0.569
Hispanic	6,344	0.204	4,534	0.211	1,615	0.186	1,654	0.201	11,141	0.197	14,905	0.199
White	6,344	**0.073**	4,534	0.084	1,615	**0.065**	1,654	0.088	11,141	**0.079**	14,905	0.137
Asian	6,344	**0.023**	4,534	0.052	1,615	**0.023**	1,654	0.048	11,141	**0.031**	14,905	0.090
Other race	6,344	0.007	4,534	0.005	1,615	0.004	1,654	0.007	11,141	**0.007**	14,905	0.005
English lang. learner	6,320	**0.070**	4,532	0.100	1,615	**0.061**	1,654	0.086	11,091	**0.067**	14,899	0.084
Free lunch	6,320	0.833	4,532	0.847	1,615	0.858	1,654	0.839	11,091	**0.814**	14,899	0.755
Student w/disabilities	6,344	**0.203**	4,534	0.224	1,615	0.200	1,654	0.175	11,141	0.181	14,905	0.173
Percent absent	6,273	**0.231**	4,422	0.203	1,564	**0.259**	1,582	0.191	10,935	**0.217**	14,419	0.142
GPA	6,408	**1.312**	4,719	1.428	1,649	**1.184**	1,709	1.457	10,457	**1.662**	14,866	2.257
Credits earned	6,428	**4.571**	4,756	4.660	1,651	**4.301**	1,709	4.731	8,489	**5.006**	11,196	5.912
Earnings in yr. before H.S. exit (in 1,000s)	4,766	3,599.84	3,230	3,523.99	1,360	3,026.13	1,430	3,097.36	8,327	3,725.39	10,730	3,697.83
Year exited - 2011	6,428	0.018	4,756	0.035	1,651	0.031	1,709	0.042	11,316	0.029	16,612	0.040
Year exited - 2012	6,428	0.064	4,756	0.097	1,651	0.156	1,709	0.126	11,316	0.113	16,612	0.224
Year exited - 2013	6,428	0.138	4,756	0.277	1,651	0.325	1,709	0.479	11,316	0.169	16,612	0.183
Year exited - 2014	6,428	0.157	4,756	0.196	1,651	0.354	1,709	0.319	11,316	0.165	16,612	0.150
Year exited - 2015	6,428	0.248	4,756	0.171	1,651	0.105	1,709	0.029	11,316	0.207	16,612	0.153
Year exited - 2016	6,428	0.173	4,756	0.116	1,651	0.019	1,709	0.004	11,316	0.145	16,612	0.120
Year exited - 2017	6,428	0.199	4,756	0.107	1,651	0.004	1,709	0.001	11,316	0.166	16,612	0.109
School characteristics												
% in online courses	6,428	**0.294**	4,756	0.176	1,651	**0.281**	1,709	0.139	11,316	**0.330**	16,387	0.202
Alternative school	5,941	**0.086**	4,021	0.073	1,479	**0.121**	1,392	0.060	10,129	**0.133**	13,445	0.053
Charter school	5,941	**0.023**	4,021	0.030	1,479	**0.033**	1,392	0.019	10,129	**0.023**	13,445	0.030
% Black	6,344	0.639	4,534	0.633	1,615	0.655	1,654	0.637	11,141	**0.658**	14,905	0.599

Table 1. (Continued).

Treatment group = took courses online in H.S.; Comparison group = no online courses in H.S.	Students who failed at least one course in H.S.				Students who failed a course and had four years of post-H.S. UI earnings information				All high school exiters			
	n	*Treatment*	*n*	*Comparison*	*n*	*Treatment*	*n*	*Comparison*	*n*	*Treatment*	*n*	*Comparison*
% Hispanic	6,344	0.209	4,534	0.202	1,615	0.199	1,654	0.194	11,141	0.198	14,905	0.200
% Asian	6,344	**0.048**	4,534	0.057	1,615	**0.043**	1,654	0.057	11,141	**0.044**	14,905	0.070
% English learners	6,344	0.089	4,534	0.090	1,615	0.088	1,654	0.086	11,141	**0.083**	14,905	0.082
% Free lunch	6,344	**0.822**	4,534	0.814	1,615	**0.837**	1,654	0.806	11,141	**0.817**	14,905	0.777
% Students w/disabilities	6,344	**0.234**	4,534	0.216	1,615	**0.228**	1,654	0.208	11,141	**0.231**	14,905	0.200
Total courses offered	6,027	**0.001659**	4,192	0.001353	1,517	**0.001903**	1,533	0.001490	10,426	**0.001978**	15,004	0.001154
Advanced courses offered	6,027	**0.000007**	4,192	0.000018	1,517	**0.000008**	1,533	0.000029	10,426	**0.000008**	15,004	0.000012
Serv. learning courses offered	6,027	**0.000002**	4,192	0.000001	1,517	**0.000005**	1,533	0.000000	10,426	**0.000010**	15,004	0.000001
CTE courses offered	6,027	**0.000041**	4,192	0.000056	1,517	**0.000046**	1,533	0.000059	10,426	**0.000039**	15,004	0.000050
School-level student mobility	6,428	**3.253**	4,756	3.187	1,651	**3.035**	1,709	3.156	11,316	**3.148**	16,612	3.245

Table 2. Descriptive information on earnings after expected high school (H.S.) exit for students who failed at least one course in high school.

		All who failed a course		Constant subsample	
Outcome measures		*Treatment*	*Comparison*	*Treatment*	*Comparison*
	N	6,298	4,646	1,635	1,709
Graduated from high school		*77.2%*	*73.5%*	*72.0%*	*79.1%*
	N	5,154	3,559	1,635	1,709
% w/earnings info 1 yr. after H.S.		*81.8%*	*76.6%*	*n.a.*	*n.a.*
% w/0 earnings 1 yr. after H.S.		*9.7%*	*9.5%*	*16.3%*	*12.5%*
Earnings yr. 1 after H.S. exit		$6,691.42	$6,588.05	$5,466.58	$6,188.89
	N	4,227	3,182	1,635	1,709
% w/earnings info 2 yrs. after H.S.		*67.1%*	*68.5%*	*n.a.*	*n.a.*
% w/0 earnings 2 yrs. after H.S.		*5.9%*	*7.7%*	*6.4%*	*5.0%*
Earnings yr. 2 after H.S. exit		$9,098.62	$9,164.16	$8,816.84	$9,993.59
	N	3,163	2,651	1,635	1,709
% w/earnings info 3 yrs. after H.S.		*50.2%*	*57.1%*	*n.a.*	*n.a.*
% w/0 earnings 3 yrs. after H.S.		*4.1%*	*5.4%*	*4.5%*	*4.4%*
Earnings yr. 3 after H.S. exit		$10,769.39	$11,179.65	$11,223.38	$12,558.07
	N	1,920	2,053	1,635	1,709
% w/earnings info 4 yrs. after H.S.		*30.5%*	*44.2%*	*n.a.*	*n.a.*
% w/0 earnings 4 yrs. after H.S.		*3.0%*	*4.1%*	*8.0%*	*6.1%*
Earnings yr. 4 after H.S. exit		$11,615.25	$12,984.51	$12,647.30	$14,309.12

there were fewer advanced and career and technical education (CTE) courses made available but where more service-learning courses were offered.

Descriptive Information on Study Outcomes

Table 2 presents descriptive information on earnings outcomes for the study samples (by treatment status) and indicates the percentage of cases each year with UI data on earnings. For the reasons described above—i.e., students leaving high school later in the study period, and possibly the absence of employer earnings reports, work in the informal sector, or moves out of state—the number of cases available for analysis declines each year. This table also distinguishes reports of *zero* earnings from the absence of reported earnings. Students who failed a course in high school and participated in online credit recovery had a higher graduation rate than those who did not repeat their courses online, and they initially (in the first year after their expected high school exit) were more likely to have reported UI earnings that were slightly higher on average than the comparison group who did not recover course credits online. By the second post-high school year, however, the comparison group who did not engage in online credit recovery was more likely to have reported UI earnings that were higher than the treatment group average, a pattern that continued into the fourth post-high school year (with a widening gap in earnings). Among the subsample of high school students who failed at least one course and had UI earnings in each of the four post-high school years (also shown in Table 2), a higher proportion of the comparison group had UI earnings and higher earnings on average in all four post-high school years.

In descriptively investigating whether missing outcome data differed by treatment status (online credit recovery), 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

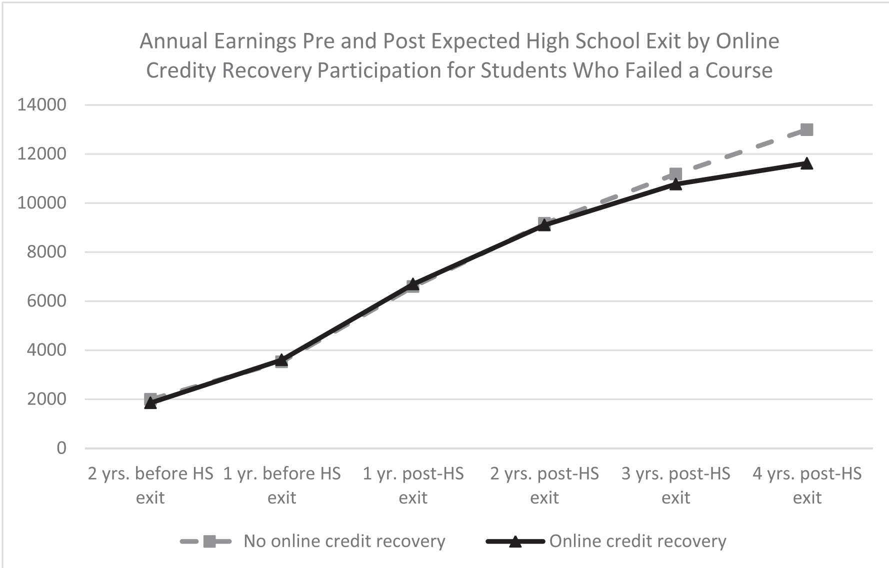


Figure 2a. Trends in Student Annual Earnings Before and After (Expected) High School Exit by Online Credit Recovery Participation for H.S. Students Who Failed a Course.

dummies as the dependent variable to predict missing outcome data, including as covariates the treatment status indicator and cohort and high school 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 entry cohort and high school exit years, students participating in online course-taking are significantly less likely to be missing earnings data. The cohort dummies confirm our expectation that students entering in later high school years are significantly more likely to be missing data on outcomes. When student characteristics controlled for in the analysis are added to these models, the treatment status (online credit recovery) dummy is no longer statistically significant in these regressions. Below, we discuss the estimation of alternative approaches to further explore the implications of missing outcome data for our analysis.

Figures 2a and 2b present the descriptive trends for student annual earnings both before and after their expected high school exit graphically, including during the final two years of high school and four years post-high school, for students with earnings data available. Figure 2a presents these trends (by online credit recovery) for all students who failed a course in high school, while Figure 2b presents these same descriptive trends for the (constant) subsample with UI earnings data in all four post-high school years. These graphs confirm the parallel trends in pre-exit earnings, and they also show the pattern of diverging earnings trajectories post-high school between online credit recovery participants and those who did not repeat courses online. Of course, these descriptive trends in earnings do not take into account the differences between students who engaged in online credit recovery and those who did not, which we adjust for in the two stage least squares (2SLS) instrumental variables (IV) estimation of the effects of online credit recovery (discussed below).

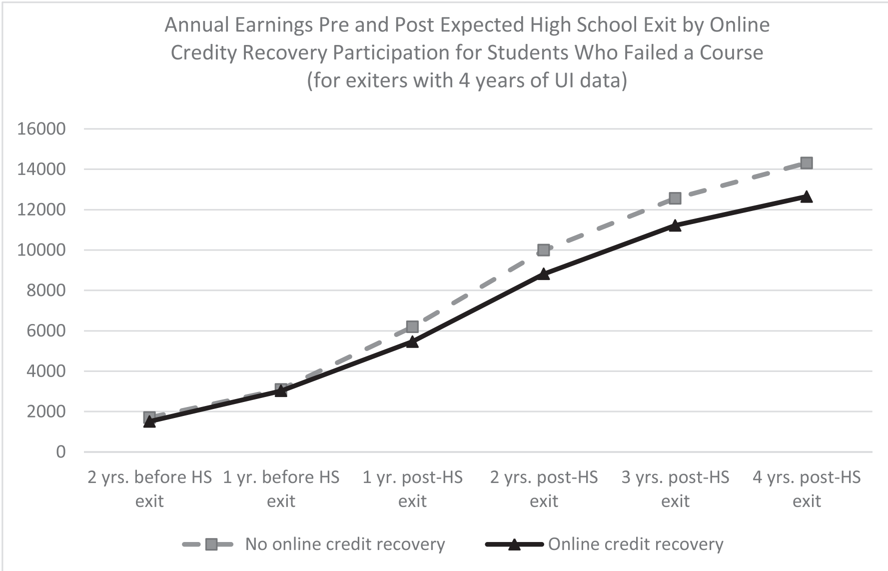


Figure 2b. Trends in Student Annual Earnings Before and After (Expected) High School Exit by Online Credit Recovery Participation for H.S. Students Who Failed a Course (Constant Subsample).

Study Methods

As described above, the large majority of students in our study district failed at least one course in high school (the average number of courses failed per student over our study period is 1.82), and more than half of these high school students repeated a course using the online credit recovery program the district adopted; the alternative is to repeat the course in the traditional classroom (face-to-face) setting. District staff conveyed that students consistently took the online credit recovery course option (over repeating a course in a traditional classroom setting) when it was available, and that the availability of online credit-recovery (and other specialty course options) depended largely on administrative and school staffing and resource decisions and varied over time within and between schools. Although this information suggests that student characteristics may be less influential in determining who engages in online credit recovery in this district, it is important to adjust for any observed and unobserved student- and school-level factors that might otherwise bias our estimation of the effects of online credit recovery on students' post-high school labor market outcomes.

Estimation Approach

In estimating the relationship between online course-taking for credit recovery and student labor market outcomes, we employ a 2SLS IV approach to account for the potential selective differences between online credit recovery participants and nonparticipants and get closer to plausibly causal estimates. Similar to Altonji (1995), Rose and Betts (2004), Gottfried and Plasman (2018), and Darolia et al. (2020), we use variation across high schools in the types of courses made available to students in each high school as our primary instruments in the first stage of the 2SLS IV model. The intent is to purge the portion of course selection that may be correlated with student abilities. We closely followed Darolia et al. (2020) in developing these instruments, because, like Darolia et al., we have administrative data on the scheduled offering and availability of courses to multiple cohorts of students attending the district high schools over the study period, which allows for the construction of course availability measures that do not incorporate variation from a given student's own course-taking behavior. The primary instruments consist of courses available to a student averaged over their time in high school (and adjusted for enrollment, i.e., availability per 100 students)—focusing on total courses and specialty courses that include advanced, CTE, and service learning/work courses—as well as a measure of access to the online credit recovery system that consists of the proportion of other students in a high school accessing the system in a given school year. Other school-level characteristics added to the first-stage model to adjust for selection into online credit recovery include school type (alternative and charter schools vs. neighborhood schools); average student mobility across schools in the district, and average student demographics (race/ethnicity, English language learners, students with disabilities, and free or reduced-price lunch eligible). Like Gottfried and Plasman (2018) and Darolia et al. (2020), we also included high school fixed effects, as well as cohort[5] and high school (expected) exit year fixed effects, in the 2SLS models to account for other unobserved school factors and cohort-specific unobserved influences on online credit recovery participation and year-specific effects on labor market outcomes.

As shown in equation (1) below, the dependent variable in the first-stage model is an indicator (binary measure) of any online course-taking for credit recovery (O_{ist}) for student i in school s whose expected year of high school exit is year t. The vector Z_{st} includes the instruments for school course offerings (and other school-level characteristics such as school type, average student demographics and mobility, etc.) described above. The first-stage model also includes student-level characteristics (X_{ist}), measured in the 9th-grade year (or other baseline school year for transfers), and cohort (ϕ_{is}) and school (ψs) fixed effects:

$$O_{ist} = \beta_0 + \beta_1 X_{ist} + \beta_2 Z_{st} + \phi_{is} + \psi s + e_{1ist}. \tag{1}$$

The cohort and school fixed effects help to account for factors that affected the ramp-up of online course-taking for credit recovery over time after it was introduced in the school district.

In the second-stage model (equation 2 below), Ž is the predicted probability of online credit recovery from the first-stage estimation, δ_2 is the estimated causal effect of online credit recovery on student labor market outcomes (Y_{ist}), and η_t are (expected high school exit) year fixed effects:

$$Y_{ist} = \delta_0 + \delta_1 X_{it} + \delta_2 \widehat{Z}_{st} + \phi_s + \psi_s + \eta_t + e_{2ist}. \tag{2}$$

The model is estimated separately for each of four years of students' post-high school earnings, as well as for three measures of post-high school employment: the number of quarters worked in the first two years after expected high school exit; the number of consecutive quarters that they had earnings in the first three years (12 quarters) after expected high school exit, and the number of consecutive quarters (of the first 12 quarters after expected high school exit) that students worked for the same employer. As indicated earlier, we also estimated the 2SLS IV models on

[5] Cohorts of students are defined by the school year they would first have had access to the online course-taking system in high school. The online course-taking system was adopted and first offered in the 2010/2011 school year.

a (constant) subsample of students who failed at least one course in high school and had no missing UI earnings records in the 16 quarters post-high school. Robust standard errors are specified.

To summarize, the identifying variation we employ to estimate δ_2 (the causal effect of online credit recovery) takes advantage of idiosyncratic differences in exposure to online course recovery both *within schools across time*, controlling for cohort and high school exit year, and *within time across schools*, controlling for school differences with school fixed effects. To assess whether the model is correctly specified and the performance of the instruments, we conduct tests for underidentification, weak identification/weak instruments, and overidentification for each 2SLS IV estimation. For the underidentification test, we report the Kleibergen-Paap rk LM statistic, where rejecting the null affirms that the excluded instruments are relevant (i.e., correlated with the endogenous regressors). We also assess the Stock-Wright LM S statistic, where, alternatively, accepting the null hypothesis would imply the overidentifying restrictions are valid. We use the Hansen J statistic to assess the validity of the overidentifying restrictions, (i.e., that they are jointly equal to zero). Finally, we test the exogeneity (or orthogonality) of several subsets of the instruments using the C-statistic,[6] where accepting the null hypothesis would imply that the full set of orthogonality conditions is valid.

STUDY FINDINGS

Main Results on Online Credit Recovery Effects

We begin by presenting a summary of the main estimated effects of online credit recovery on earnings post-high school (from the 2SLS IV models) in Table 3. Focusing first on the sample of students who failed a course in high school (panel A), the estimated effects of online credit recovery are negative in sign, and the gap or difference in earnings between online credit recovery participants and nonparticipants increases in magnitude (and is negative) each subsequent year. However, only the estimated effect on earnings in the fourth year post high school—a negative differential of nearly $3,000—is statistically significant. When the study sample is restricted to the (constant) subsample of students who had no missing UI-reported earnings in each of the four years post high school (panel B), we see the same pattern in estimated effects, although the negative effects are larger and statistically significant in both the third and fourth years post high school (a difference of approximately $4,000 by year four). Figures 3a and 3b present these results graphically with the (robust) standard error bars.

Table 3 also presents information on the performance of the 2SLS IV models. We report p-values associated with the test statistics for the three main tests: model underidentification (Kleibergen-Paap rk LM statistic), weak instruments (Stock-Wright LM S statistic), and overidentification (Hansen J statistic). The p-values associated with the Kleibergen-Paap rk LM statistic clearly reject the null hypothesis that the model is underidentified for each year of post-high school earnings (i.e., chi-square values ranging from 135 to 888 for the models in panels A and B). The weak instruments tests—both the Stock-Wright LM S statistic and Hansen J statistic—likewise confirmed that the overidentifying restrictions are valid for each of the

[6] The C-statistic is defined as the difference of the Sargan-Hansen statistic of the equation with the smaller set of instruments and the equation with the full set of instruments, i.e., including any instruments whose validity is questionable. Under the null hypothesis, both the smaller set of instruments and the additional, questionable instruments are valid.

Table 3. Instrumental variables (IV) estimated effects of online credit recovery on post-high school earnings (based on expected H.S. exit year).

Treatment = Took courses online for credit recovery in high school

Panel A	Post-H.S. earnings			
Failed at least one course in high school	1 yr. post	2 yrs. post	3 yrs. post	4 yrs. post
N	6,278	4,842	3,546	2,249
Estimated effect	$-249.22	$-306.88	$-609.05	**$-2971.44**
Robust standard error	(347.44)	(563.19)	(900.03)	(1,428.86)
Underidentification test p-value	0.000	0.000	0.000	0.000
Weak instrument test p-value	0.922	0.549	0.277	0.144
Overidentification test p-value	0.918	0.504	0.297	0.510
Centered R^2	0.278	0.149	0.132	0.143

Panel B	Post-H.S. earnings			
Failed at least one course in high school - constant subsample	1 yr. post	2 yrs. post	3 yrs. post	4 yrs. post
N	2,141	2,141	2,141	2,141
Estimated effect	$-674.88	$-1,696.47	**$-2,713.71**	**$-4,032.80**
Robust standard error	(611.03)	(916.74)	(1,170.87)	(1,276.68)
Underidentification test p-value	0.000	0.000	0.000	0.000
Weak instrument test p-value	0.766	0.316	0.399	0.149
Overidentification test p-value	0.793	0.365	0.565	0.533
Centered R^2	0.246	0.132	0.109	0.113

Notes: Coefficient estimates in boldface are statistically significant at $\alpha = 0.05$. The student and school covariates included in the first-stage IV (2SLS) models are indicated in Table 4. Test statistics reported in the table are:

- Underidentification test (null: equation is weakly identified): Kleibergen-Paap rk LM statistic
- Weak instrument test (null: overidentifying restrictions are valid): Stock-Wright LM S statistic
- Overidentification test (of joint significance of endogenous regressors): Hansen J statistic

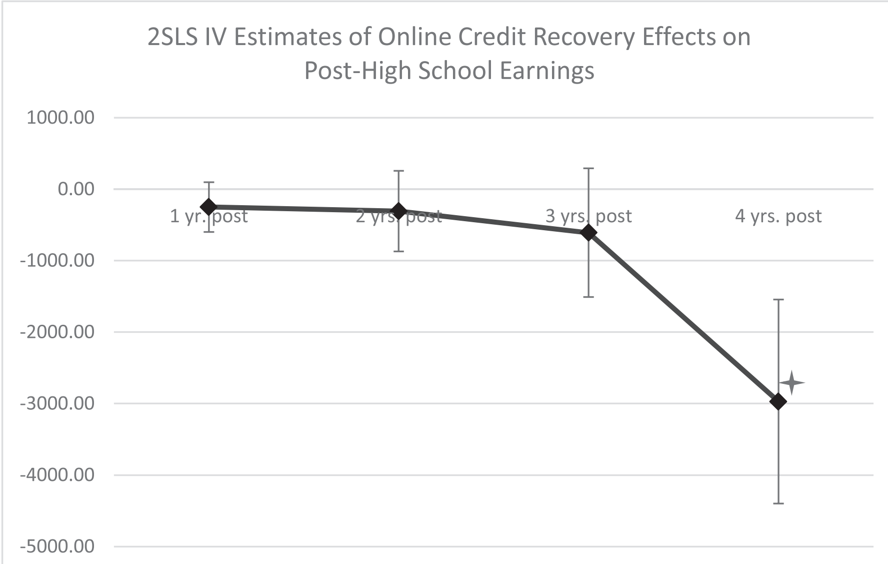
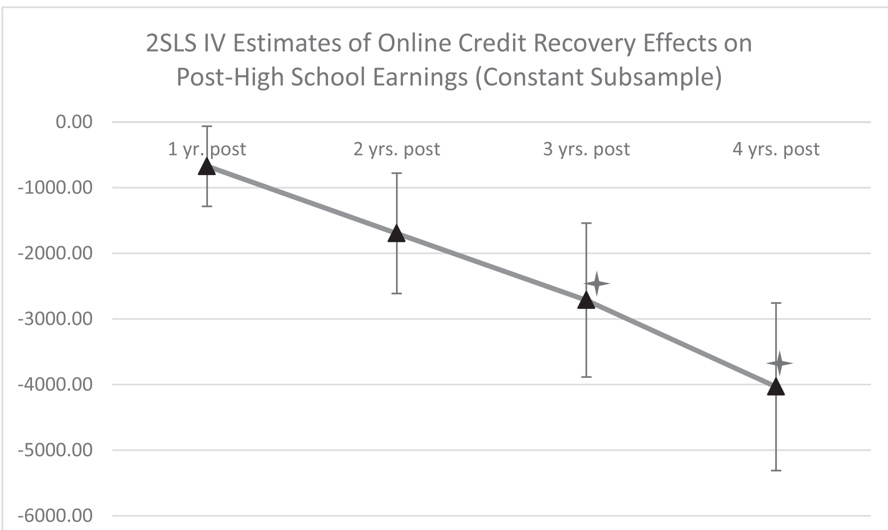


Figure 3a. Instrumental Variables (2SLS) Estimates of Online Credit Recovery Effects on Post-High School Earnings for High School Exiters.



Notes: Standard error bars are included for each estimate of post-high school earnings. See Table 3 for a tabular summary of these results and notes on the estimation. The symbol indicates a statistically significant coefficient estimate.

Figure 3b. Instrumental Variables (2SLS) Estimates of Online Credit Recovery Effects on Post-High School Earnings for Subsample of H.S. Exiters with No Missing UI Earnings. Information in Four Post-H.S. Years.

models presented in panels A and B. The results of the C tests indicated that the null hypothesis implying that the full set of orthogonality conditions is valid was not rejected.[7]

We also present the first-stage model results from the 2SLS IV estimation model of earnings in the first year post high school for students who failed a course in high school and the subsample with no missing earnings reports in Table 4. The results suggest that school-level characteristics were among the most important factors predicting student participation in online credit recovery, particularly the percentage of other students taking online courses and the measures (instruments) for course availability for advanced and CTE courses, as well as average student body characteristics and school mobility (and high school cohort indicators). The results are generally similar for all students who failed a course in high school and for the subsample with no missing earnings reports across the four post-high school years.

Estimated Effects on Employment

To better understand the observed post-high school earnings differences between students who participated in online credit recovery in high school and those who failed a course in high school but did not repeat courses online, we estimated the number of quarters worked in the first two years after expected high school exit, the number of consecutive quarters that they had earnings in the first three years (12 quarters) after expected high school exit, and the number of consecutive quarters (of the first 12 quarters after expected high school exit) that students worked for the same employer. Simple descriptive statistics showed that online credit recovery participants worked 5.88 of 8 quarters in the first two post-high school years compared to 5.73 of 8 quarters for nonparticipants (a statistically significant difference), while there were no statistically significant differences in the number of consecutive quarters that they had earnings in the first three post-high school years (7.04 vs. 7.02 consecutive quarters on average, respectively). Alternatively, online credit recovery participants had significantly fewer quarters working consecutively for the same employer in the first three post-high school years (4.58 vs. 4.74 consecutive quarters, respectively).

Table 5 presents the results of the 2SLS IV estimation of the effects of online credit recovery on these post-high school employment outcomes. The tests for model underidentification, weak instruments, and overidentification were likewise all satisfied for the employment models; that is, the instruments (overidentifying restrictions) are valid and not weak. The 2SLS IV analysis results show that among students who failed a course in high school, there are no statistically significant differences in the likelihood of being employed or the likelihood of retaining employment for online credit recovery participants compared to nonparticipants in the four post-high school years. The sign on the treatment coefficients changes from positive to negative when we restrict the analysis to the subsample of students who had UI earnings in all four post-high school years, but the estimates are all imprecise. Thus, the

[7] The C tests of the orthogonality conditions were conducted (separately) for the following subsets of instruments included in the first-stage model: (i) the four measures of courses available to students averaged over their time in high school and adjusted for enrollment (total courses, advanced courses, CTE courses, and service learning/work courses); (ii) the proportion of other students in high school accessing the online credit recovery system in a given school year; (iii) the school type and average school demographic characteristics, including student mobility; and (iv) the (entry) cohort indicators. The p-values associated with the C test statistic for each subset of instruments (which failed to reject the null) were: (i) 0.323, (ii) 0.285, (iii) 0.539, and (iv) 0.985, respectively.

Table 4. First-stage instrumental variables model results.

Predicting participation in online course-taking	High school exiters - failed at least one course (n = 6,278)			Failed a course - no missing outcome data (n = 2,141)		
Student characteristics	Coefficient	Std. error	p-value	Coefficient	Std. error	p-value
Female	0.016	0.009	0.078	−0.004	0.008	0.599
Asian	**−0.080**	0.030	0.008	0.007	0.019	0.727
White	**−0.048**	0.017	0.005	**−0.046**	0.017	0.006
Hispanic	−0.026	0.014	0.058	−0.012	0.013	0.334
Other race	0.023	0.044	0.598	−0.027	0.043	0.536
English lang. learner	**−0.047**	0.020	0.018	−0.016	0.018	0.369
Free lunch eligible	0.013	0.012	0.259	−0.009	0.011	0.407
Student w/disabilities	−0.019	0.012	0.109	−0.004	0.011	0.669
Percent absent	**−0.080**	0.031	0.010	−0.048	0.030	0.112
GPA	**−0.109**	0.010	0.000	**−0.045**	0.009	0.000
Credits earned	**0.011**	0.003	0.000	**0.008**	0.003	0.007
Earnings yr. before expected HS graduation (in 1,000s)	0.00003	0.00111	0.763	0.00131	0.00097	0.161
School characteristics						
% students taking online courses	**1.005**	0.064	0.000	**0.512**	0.112	0.000
% Black	**−0.421**	0.205	0.040	**−0.869**	0.318	0.006
% Hispanic	**−0.688**	0.287	0.016	**−1.137**	0.420	0.007
% Asian	**−1.380**	0.352	0.000	**−1.465**	0.371	0.000
% English lang. learners	**0.745**	0.200	0.674	**0.584**	0.272	0.032
% Free lunch eligible	−0.126	0.145	0.387	−0.519	0.299	0.261
% Student w/disabilities	0.285	0.217	0.191	**0.533**	0.184	0.083
Total courses offered	**43.0**	15.3	0.005	**30.1**	8.6	0.001
Advanced courses offered	**2,149.0**	654.7	0.001	**2,367.8**	854.8	0.006
Serv. learning courses offered	217.3	241.2	0.368	−365.2	281.5	0.195
CTE courses offered	**1,369.4**	173.6	0.000	**1,912.1**	235.4	0.000
Alternative school	0.018	0.136	0.896	**−0.253**	0.105	0.016
Charter school	**−0.306**	0.117	0.009	−0.085	0.102	0.407
School-level student mobility	**0.217**	0.034	0.000	**−0.110**	0.053	0.038
Entry cohort - 2011	**−0.310**	0.017	0.000	**−0.174**	0.025	0.000
Entry cohort - 2012	**−0.485**	0.024	0.000	**−0.165**	0.034	0.000
Entry cohort - 2013	**−0.389**	0.027	0.000	**−0.121**	0.037	0.001
Entry cohort - 2014	**−0.327**	0.029	0.000	**−0.120**	0.043	0.006
Entry cohort - 2015	**−0.099**	0.035	0.005	**0.019**	0.079	0.809
Entry cohort - 2016	−0.002	0.046	0.968	**0.503**	0.073	0.000
Entry cohort - 2017	**−0.286**	0.045	0.000	omitted		
Centered R-squared, Model F	51.26%	F = 968		87.15%	F = 6373	

Notes: Coefficient estimates in boldface are statistically significant at $\alpha = 0.05$. School and year fixed effects coefficient estimates are not presented.

increasingly negative differential in estimated earnings for online credit recovery participants observed in the post-high school years may be more likely driven by lower wages received on the job (or a slower rate of increase in earnings compared to those who did not participate in online credit recovery) than by their employment rates.

Table 5. Instrumental variables (IV) estimated effects of online credit recovery on post-high school employment outcomes (based on expected H.S. exit year).

Treatment = Took courses online for credit recovery in high school			
Panel A	Post-H.S. employment outcomes		
Students who failed at least one course in high school	No. of qtrs. worked in first 2 years post-H.S.	No. of consecutive qtrs. worked post-exit	No. of consecutive qtrs. worked for one employer
N	4,412	3,778	3,778
Estimated effect	0.051	0.178	0.217
Robust standard error	(0.121)	(0.282)	(0.231)
Underidentification test p-value	0.000	0.000	0.000
Weak instrument test p-value	0.269	0.512	0.199
Overidentification test p-value	0.228	0.475	0.510
Centered R^2	0.131	0.123	0.192
Panel B			
Students who failed at least one course in high school - constant subsample	No. of qtrs. worked in first 2 years post-H.S.	No. of consecutive qtrs. worked post-exit	No. of consecutive qtrs. worked for one employer
N	2,090	1,968	2,138
Estimated effect	−0.060	−0.032	−0.353
Robust standard error	(0.246)	(0.234)	(0.430)
Underidentification test p-value	0.000	0.000	0.000
Weak instrument test p-value	0.795	0.507	0.804
Overidentification test p-value	0.764	0.437	0.754
Centered R^2	0.205	0.132	0.133

Notes: Coefficient estimates in boldface are statistically significant at $\alpha = 0.05$. The student and school covariates included in the first-stage IV (2SLS) models are shown in Table 4. Test statistics reported in the table are:
- Underidentification test (null: equation is weakly identified): Kleibergen-Paap rk LM statistic
- Weak instrument test (null: overidentifying restrictions are valid): Stock-Wright LM S statistic
- Overidentification test (of joint significance of endogenous regressors): Hansen J statistic

Estimated Effects Adjusting for Missing Data on Outcomes

The sample sizes reported in Table 2 confirm that the number of earnings records available decreases with each year post high school; the high UI earnings data match rate (nearly 99 percent) implies that this is largely because later earnings data are not available for students leaving high school in more recent school years. However, as we also noted, UI earnings data could also be missing because the student moved out of the state after high school or worked in the informal sector, or the employer did not report earnings information. The initial exploration of missing data discussed above suggests that students who engaged in online credit recovery were less likely to be missing data, possibly associated with lower geographic mobility; however, after adding control variables for student characteristics to the models, the differences were 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 (Hotz & Scholz, 2002; Kornfeld & Bloom, 1999). 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. (2017) suggest that administrative data are less likely to miss these newer types of self-reported earnings than are survey data.

To further address potential concerns about missing data on earnings, we first estimated 2SLS IV models of the effects of online credit recovery using measures of post-high school earnings in which missing earnings data were replaced with zeros (assuming zero earnings for a quarter in which earnings were missing). The results showed the same general patterns in estimated effects and statistical significance of the estimates as in the primary models for students who failed a course in high school; all estimated effects of online credit recovery were negative, although, as expected, the magnitudes of the effects were smaller (ranging from $-746 to $-1,937). In addition, we also estimated the probability of appearing in a given year of UI earnings data for each student (using the available student-level characteristics shown in Table 1) and subsequently included inverse probability weights in the second-stage 2SLS IV model as an alternative method to assess the implications of the missing data on outcomes. The inverse probability weights were not statistically significant in any of the four post-high school earnings models and did not alter the pattern in estimated online credit recovery effects or the performance of the 2SLS IV models (i.e., validity of the instruments).

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.

DISCUSSION AND CONCLUSION

In framing this analysis based on theory and existing research evidence, we hypothesized that high school students engaging in online credit recovery (vs. repeating courses in traditional classroom settings) would likely have comparable earnings when first entering the labor market post high school, in accord with the expectations set out by signaling (or sorting) theories given that participation in online credit recovery is not observed on student transcripts. However, human capital theory would predict that if high school online credit recovery courses are inferior in terms of the knowledge or skills they impart and that learning is critical to workplace productivity, online credit recovery participants may earn less (or see slower growth in earnings) in the labor market over time, particularly if employers subsequently observe that these students perform relatively more poorly on the job.

Indeed, this plausibly causal explanation appears to be consistent with the findings generated in this study. High school students who failed a course in high school and engaged in online credit recovery initially had comparable earnings to those who did not participate in online credit recovery (negative but statistically insignificant earnings differentials in the first couple of years after exiting high school), but the gap became larger and statistically significant by the fourth post-high school year.

These findings are consistent with the research of Arcidiacono, Bayer, and Hizmo (2010), who found that ability is gradually revealed over time in the labor market for high school completers, implying that the signaling value of a high school diploma will wane as knowledge about worker productivity is gained. They also echo the findings of Altonji and Pierrett (2001), who likewise concluded that wages become more closely tied to productivity and less dependent on readily observable characteristics or credentials with time in the labor market. In addition, the concerns about human capital forgone in online credit recovery courses resonate with those of earlier studies of the GED (Cameron & Heckman, 1993, p.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 found that the wages of GED recipients were significantly lower than those of high school graduates and were closer to those of high school dropouts. Consistent with the more recent findings of Clark and Martorell (2014), they determined that human capital (or productivity differences) rather than signaling value explained wages earned by those obtaining a high school degree.

That said, in light of prior research suggesting that online credit recovery may be a comparatively inexpensive option for increasing the probability that high school students graduate from high school, it may be viewed favorably by some that, at least initially, online credit recovery participants did not appear to earn much less in post-high school earnings, and statistically significant differences were not observed in their rate of post-high school employment or employment retention. Heinrich and Darling-Aduana (2021) found that online credit recovery programs in this same school district not only cost about half that of recovering course credits in a traditional classroom setting, but online credit recovery may also be about 8 to 30 times more cost-effective in raising graduation rates than alternative interventions (Levin, 2009). 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. Thus, with the potential push they give to high school graduation rates (a federally tracked performance measure), online credit recovery programs may be a cheap "fix" that will be difficult for budget-constrained school districts to let go.

We still maintain that our findings suggest some caution is in order for 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. Because this is the first study we know of to follow high school students taking courses online for credit recovery into the labor market and it is limited to a single, large urban school district, it is important to further examine in other contexts whether online credit recovery may be associated with lower human capital accumulation. 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 other important limitations of this research that need to be acknowledged or reiterated. First, while the large urban school district we studied 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 the 2SLS IV strategy for empirical estimation appeared to work well in adjusting for student selection into online credit recovery in this district, the potential threats to validity associated with unobserved characteristics of high schools and high school students and the missing outcomes data suggest caution is warranted in drawing conclusions about point estimates and longer-term earnings trends from this analysis.

CAROLYN J. HEINRICH is the Patricia and Rodes Hart Professor of Public Policy, Education, and Economics at Vanderbilt University, Peabody College of Education and Human Development, Department of Leadership, Policy, and Organizations, 202 Payne Hall, PMB 414, 230 Appleton Place, Nashville, TN 37203 (e-mail: carolyn.j.heinrich@vanderbilt.edu).

HUIPING (EMILY) CHENG is an Associate Researcher at the Wisconsin Center for Education Research at the University of Wisconsin at Madison, 1025 West Johnson Street, Suite 785, Madison, Wisconsin 53706 (e-mail: hcheng6@wisc.edu).

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DATA AVAILABILITY STATEMENT

This paper uses confidential, student-level data from the Wisconsin Department of Workforce Development, the Wisconsin Department of Public Instruction, and Milwaukee Public Schools. The linking of the administrative data was undertaken through access to the Wisconsin Administrative Data Core maintained by the Institute for Research on Poverty at the University of Wisconsin–Madison. These data can be obtained by completing an application to Milwaukee Public Schools Research and Evaluation office (https://mps.milwaukee.k12.wi.us/en/District/Initiatives/Research-Development/Conducting-Research-in-MPS.htm) and seeking approval for the matching and linking of Wisconsin administrative data from the Institute for Research on Poverty. The first author is willing to assist with the steps in this process (Carolyn J. Heinrich, carolyn.j.heinrich@vanderbilt.edu).

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