

**Does the Labor Market Give Credit for Learning Online?  
Online Course-taking in High School and Later Labor Market Outcomes**

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**Abstract**

A growing 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 the expectations of signaling or sorting theories hold, employers would likely see high school completion as a signal that graduates have attributes that would make them good workers (not necessarily related to anything that they learned in their high school courses). However, if high school courses taken through online credit recovery are inferior in terms of the knowledge or skills they impart, and this learning is critical to workforce success, as human capital theory predicts, then online course-takers would be expected to earn less over time. The study findings suggest that high school graduates who took courses online in high school, particularly those who were recovering failed 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 grew over time, particularly for males. In addition, high school graduates (both males and females) 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.

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## **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 20<sup>th</sup> 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 Campbell’s Law.<sup>1</sup> Dynarski and others (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

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<sup>1</sup> 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.”

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. A growing 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<sup>2</sup>, 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 10<sup>th</sup> graders and two-thirds of high school seniors typically combine work and school (Rothstein, 2007).<sup>3</sup> 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

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<sup>2</sup> <https://www.childtrends.org/indicators/youth-employment>, accessed Aug. 18, 2019.

<sup>3</sup> Federal law constrains work hours of 14-15 year olds, but students age 16 and older can work unlimited hours.

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, intended to recover failed credits and support high school completion, for student 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.

### **Theory and empirical evidence that inform 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).

#### *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).<sup>4</sup> 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

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<sup>4</sup> 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.

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 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.

#### *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.

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 (in credit recovery programs) potentially improves students' post-high school labor market outcomes.

### *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 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 both during and following high school, sample sizes of students with earnings in the fourth year (pre- or post high school) are considerably smaller. As in Altonji's (1995) study, the analysis sample is restricted to students who graduated from high school.

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 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. That is, employers 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 course-taking in traditional classroom settings, 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 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.<sup>5</sup> 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<sup>6</sup> 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.

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<sup>5</sup> We empirically examine these relationships again with the analytic sample used in this study.

<sup>6</sup> [http://collegeaffordability.urban.org/covering-expenses/working-during-college/#/federal\\_work\\_study](http://collegeaffordability.urban.org/covering-expenses/working-during-college/#/federal_work_study).

## **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).

### *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. 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.<sup>7</sup> 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

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<sup>7</sup> The subsample of data with matched student record-technology vendor data is representative of all students taking courses online in this school district.

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 six years of post-high school earnings data are available for each student, which varies according to the years in which the students entered and completed 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.



### *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 on the subsample of students for whom it is possible to verify that they have completed high school. Among this subsample of high school graduates (and in the broader sample frame), approximately 37 and 39 percent of students (respectively) took a course online sometime during the years they were enrolled in high school. A subsample of high school graduates that was restricted to students who had failed at least one course during high school (about half of the high school graduates, or 49%)—*of which 56 percent participated in online course-taking*—was also defined in order to create a more similar comparison group and reduce the threat of omitted variable bias in the analyses.<sup>8</sup> Table 1 presents basic descriptive measures of the characteristics of our sample frame and subsamples used in the earnings analysis.

As shown in Table 1, 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-graduation* workforce participation and earnings. In addition to the timing of graduation, data missing 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)

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<sup>8</sup> 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 reduces the sample size to a highly selective (disadvantaged) group of students.

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 graduation 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 graduation 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 this analysis.

### *Methods*

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 9<sup>th</sup> and 10<sup>th</sup> 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. Because the primary analysis sample is limited to high school graduates in this study, we are not measuring the effects of online course-taking on high school completion. In prior work (Heinrich and

Darling-Aduana, 2019), we have shown that participation in online course-taking for credit recovery is associated with higher rates of high school graduation in this school district. The descriptive statistics in Table 1 indicate that *among students who failed at least one course in high school* (see the second set of two columns), a higher proportion (about 2.5% more) of those who took courses online (vs. those who did not) graduated from high school.

### *Descriptive analysis*

The descriptive analysis also pointed to a number of statistically significant differences between students taking courses online in high school and the comparison sample. Focusing on the last 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), but there is no difference in free lunch eligibility among 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, 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. Figure 1 also shows largely parallel trends in (quarterly) earnings during high school between online course-takers and those without online courses.

Figures 2 and 3 (for high school graduates and high school graduates who failed a course, respectively) present the descriptive trends for student annual earnings both during and after high

school, including three years during high school and five years post-high school, for students with earnings data available in those years. These graphs confirm the parallel trends in pre-graduation earnings for both subsamples of students, and they also show a pattern of diverging earnings trajectories post-high school between online course-takers and those who did not take courses online. 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). 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. In addition, for the subsample limited to high school graduates who failed a course, the fifth year post-high school earnings data are available for only a small number of cases ( $n=210$ ) at this time, so the fifth year of post-high school earnings data is not used in any of these subsequent analyses.

### *Estimation approaches*

In estimating the relationship between online course-taking and student outcomes, we adjust for these 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, career and technical

education) 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). 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 9<sup>th</sup> 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 ( $Y_{is}$ ):

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

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

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 career and technical education) taken by students in high school  $s$  in a given year,  $\phi_s$  is the proportion of students in school  $s$  taking courses online in a given year, and  $\rho_t$  is the year of high school graduation. In the second-stage model,  $\delta_3$  is the estimated causal effect of online course-taking on student outcomes ( $Y_{is}$ ),  $\psi$  are school-level characteristics, and  $\eta_t$  is the graduation year.

Following each 2SLS estimation (specifying robust standard errors), Wooldridge's robust score test of overidentifying restrictions is performed to assess if the estimating equation is correctly specified or the instruments are uncorrelated with the structural error term.<sup>9</sup>

The 2SLS IV models are estimated for high school graduates for each post-high school year of earnings and separately for the subsample of high school graduates who failed a course during high school. In addition, the models are estimated (for both of these subsamples) separately for high school graduates who ever enrolled in college and for those who were not observed during the study time period enrolling in college, as well as separately for males and

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<sup>9</sup> 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.

females. 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 career and technical education 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). 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 a high value of 425 for the estimation with high school graduates and earnings in the first year post-high school as the outcome, to a value as low as approximately 50 in models with the restricted subsamples (i.e., students who had failed a course in high school and enrolled or not enrolled in college) and the later earnings outcomes (with fewer observations). Even the lower F-statistic values exceeded the thresholds suggested by Stock et al. (2002) for strong instruments. In addition, 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 did not reject the null hypothesis, which suggests the models were correctly specified and the instruments were uncorrelated with the error term. First-stage model results for the two primary analytic samples (for models estimating earnings in the first year post-high school) are shown in Appendix A.

## **Study findings**

A summary of the estimated effects of online course-taking from the 2SLS IV models and OLS regression models are presented in Table 2. 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*. There are also no statistically significant difference in the number of quarters students worked in the first two years after high school graduation (see Figure 4 for a graphical summary of these results across all 2SLS IV model specifications). However, the trend in both the OLS regression and 2SLS IV models is toward an increasingly negative effect of online course-taking in high school that becomes larger and statistically significant by the third year post-graduation. The models estimated separately for students who ever enrolled in college after graduation and those without any college enrollment suggest that the negative effect is considerably larger when comparing students with and without online course-taking who enrolled in college. The annual earnings decrement for these young adults is greater than -\$3,000 in the third and fourth years following high school graduation.

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, but the estimated effects are nearly all negative in sign. Again, the effects of online course-taking on earnings turn increasingly negative and statistically significant in the third year post-high school, implying an earnings gap of more than -\$4,000 for those who enrolled in college; the estimate for the fourth year post-high school (for college enrollees) is statistically significant at  $\alpha < 0.10$ . 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) show the same patterns in effects, but none of the estimates are statistically significant (see Appendix B).

Descriptive analyses, OLS regressions and 2SLS IV estimates of the number of quarters worked in the third year following high school graduation (available from the author) show a negative relationship between online course-taking and the number of quarters worked in this



year, but the estimates are not statistically significant. This suggests that the negative estimated differential in earnings is likely driven more by lower earnings on the job than less workforce participation. Figures 5 and 6 present the results graphically, with Figure 5 depicting the estimated effects for all high school graduates and separately for those who failed a course, and Figure 6 showing these results by college enrollment as well. Figure 5 shows that especially for the more disadvantaged students who failed at least one course in high school (and had lower GPAs and were absent more often), there are no gains from online course-taking for credit recovery, and potentially a growing penalty over time in terms of their post-high school earnings (compared to their peers who did not take courses online). Figure 6 makes it apparent that the large negative differential in earnings for online course-takers is experienced primarily by young adults who enrolled in college after high school. In addition, although not statistically significant, the estimated effect of online course-taking on the number of quarters worked in the third year post-high school was negative and larger in magnitude for those who enrolled in college vs. who did not enroll (i.e., -0.254 vs. -0.057). In related research (Heinrich and Darling-Aduana, 2019), we found that students who took courses online in high school enrolled in poorer quality postsecondary institutions (than those who did not take courses online), which were more likely to have open admissions and lower average retention and completion rates. This also suggests that the small increase in college enrollment associated with online course-taking in high school that Heinrich and Darling-Aduana (2019) identified may not ultimately lead these students to improved long-term earnings and employment trajectories.

#### *Estimated effects by gender*

The 2SLS IV models were also estimated separately for male and female high school graduates, including for the subsamples of high school graduates who failed a course during high

school and by whether the high school graduates ever enrolled in college during the study time period. The estimated effects of these analyses by gender are shown in Table 3, and subsets of them are graphically shown in Figures 7 and 8. The results show similar patterns of post-high school graduation earnings (to the overall sample estimates), turning negative (or more negative) after the first two years post-high school for online course-takers, although males fared more poorly in their labor market earnings (in the magnitude of the negative coefficients) compared to females (see Figure 7). In addition, both male and female online course-takers who enrolled in college after high school graduation experienced larger, steady decrements in post-high school earnings (although again, not statistically significant at  $\alpha=0.05$ ). 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 earnings estimates compared to those who did not take courses online (see Figure 8).

#### *Estimated effects adjusting for missing data on outcomes*

The samples sizes reported in Table 2 confirm, as discussed earlier, 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 were less likely to be missing data, possibly associated with lower mobility; however, after adding the control variables 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 the UI data consist of 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 4, 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). Figure 9 shows graphically that these same patterns in estimated effects also emerge by whether the students ever enrolled in college after graduating, although we disregard the earnings estimates for the fourth year post-high school, given that only 15 percent of the observations included in the analysis had UI earnings reports. Those who ever failed a course in high school and went on to enroll in college again appear to fare 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 at least for the first two subgroups, 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, 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 taking courses through credit recovery, in accord with the expectations set out by signaling or sorting theories. As 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 through online 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, we saw in prior research that students who took courses online in high school enrolled in poorer quality postsecondary institutions. Although there were also gaps (negative) in the number of quarters employed following high school (for online course-takers vs. those without online course-taking) that were larger for those who enrolled in college, these differences in estimated effects were not statistically significant.

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 50 to 200 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. Yet 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 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.

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**Table 1: Descriptive Statistics for Analysis Samples**

*Treatment group=Took courses online in high school*

*Comparison group=did not take online courses in high school*

	Full sample		Failed a course		High school grads		H.S. grad + failed course	
	<i>Treatment</i>	<i>Comparison</i>	<i>Treatment</i>	<i>Comparison</i>	<i>Treatment</i>	<i>Comparison</i>	<i>Treatment</i>	<i>Comparison</i>
<b>N</b>	23,911	27,461	15,216	10,258	9,231	12,725	5,219	3,331
Female	0.467	0.505	0.444	0.447	0.510	0.552	0.478	0.508
Asian	0.028	0.087	0.021	0.050	0.036	0.098	0.028	0.058
White	0.077	0.125	0.070	0.077	0.083	0.146	0.076	0.084
Hispanic	0.193	0.209	0.198	0.217	0.196	0.192	0.200	0.197
Other race	0.008	0.007	0.008	0.007	0.007	0.005	0.007	0.004
Eng. lang. learner	0.078	0.112	0.078	0.123	0.065	0.075	0.064	0.084
Free lunch	0.817	0.767	0.838	0.858	0.811	0.738	0.823	0.837
Student w/disabilities	0.221	0.219	0.248	0.272	0.165	0.142	0.181	0.173
Percent absent	0.247	0.173	0.263	0.255	0.169	0.089	0.185	0.125
GPA	1.487	2.102	1.186	1.293	1.853	2.488	1.475	1.720
Worked before HS exit	0.794	0.792	0.796	0.771	0.796	0.796	0.796	0.772
Wkd. 2nd yr. before HS exit	0.700	0.682	0.706	0.678	0.676	0.668	0.679	0.667
Earnings yr. before HS exit	3532.83	3431.11	3598.64	3272.60	3566.63	3456.81	3594.60	3277.55
Earnings 2nd yr. before HS exit	2140.9	1943.95	2191.89	2009.82	1923.69	1821.61	1950.95	1873.49
% online users in HS	0.327	0.305	0.304	0.201	0.308	0.143	0.278	0.152
Failed a course in HS	0.789	0.458	n.a.	n.a.	0.727	0.355	n.a.	n.a.
HS graduate	0.460	0.493	0.409	0.384	n.a.	n.a.	n.a.	n.a.
Year graduated - 2012	n.a.	n.a.	n.a.	n.a.	0.081	0.228	0.026	0.031
Year graduated - 2013	n.a.	n.a.	n.a.	n.a.	0.141	0.183	0.102	0.294
Year graduated - 2014	n.a.	n.a.	n.a.	n.a.	0.162	0.156	0.141	0.217
Year graduated - 2015	n.a.	n.a.	n.a.	n.a.	0.197	0.144	0.233	0.147
Year graduated - 2016	n.a.	n.a.	n.a.	n.a.	0.196	0.150	0.233	0.161
Year graduated - 2017	n.a.	n.a.	n.a.	n.a.	0.224	0.137	0.265	0.149

**Table 2: OLS and Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings and Employment for High school Graduates**

*Treatment=Took courses online in high school*

	<b>High school graduates</b>				
Post-H.S. earnings and employment	N	<i>OLS</i>	<i>IV</i>	<i>Enrolled college - IV</i>	<i>No college - IV</i>
1 yr. after graduation	8,835	193.37	473.01	441.68	-504.55
2 yrs. after graduation	6,005	-34.52	143.57	-83.52	-911.31
3 yrs. after graduation	3,473	-233.19	<b>-1806.24</b>	<b>-3808.76</b>	-245.94
4 yrs. after graduation	1,692	-367.71	<i>-1776.34</i>	<b>-3296.30</b>	<i>-1913.44</i>
# qtrs. worked - 2 yrs. post	5,965	0.033	0.067	-0.036	-0.034
	<b>High school graduate + failed course</b>				
Post-H.S. earnings and employment	N	<i>OLS</i>	<i>IV</i>	<i>Enrolled college - IV</i>	<i>No college - IV</i>
1 yr. after graduation	4,720	111.72	-415.08	-516.91	-508.24
2 yrs. after graduation	3,250	44.99	-556.86	-1117.51	-541.07
3 yrs. after graduation	1,892	-193.08	-1811.22	<b>-4237.47</b>	-833.13
4 yrs. after graduation	954	-815.59	-2175.58	-3416.41	-3696.91
# qtrs. worked - 2 yrs. post	3,228	0.063	-0.0004	-0.165	0.060

Notes: Coefficient estimates in boldface are statistically significant at  $\alpha=0.05$ . 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 3: Instrumental Variables Regression Estimates by Gender of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates**

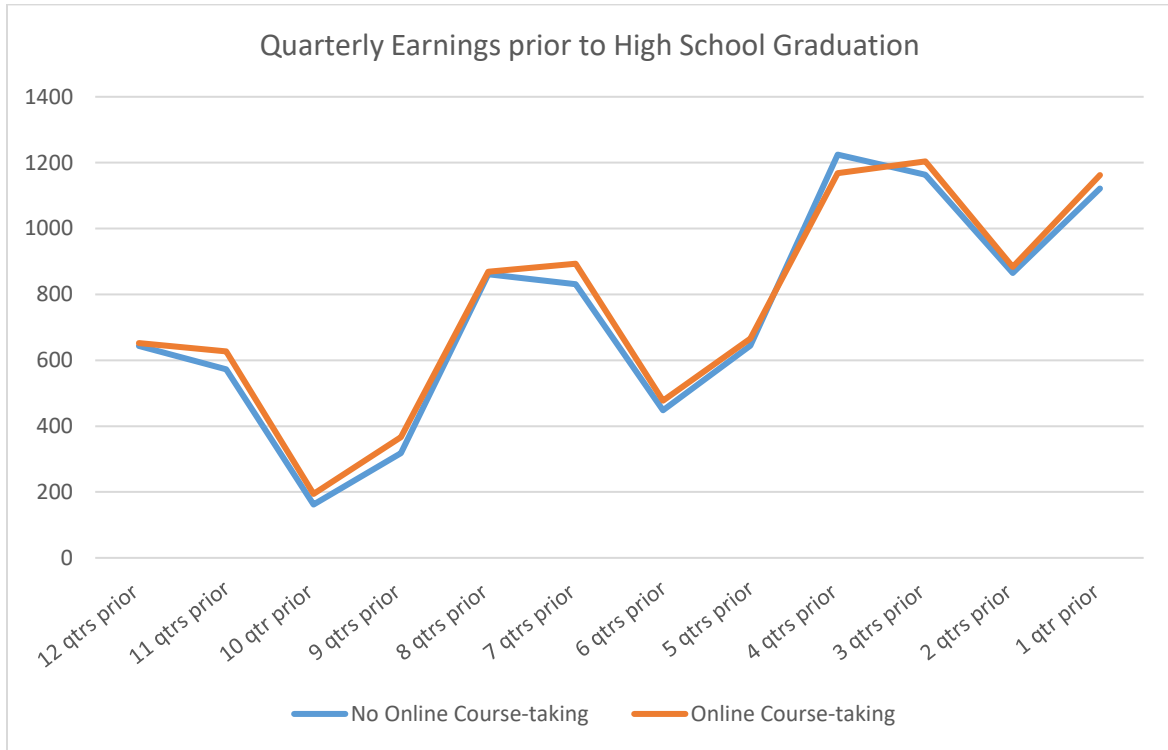
<b>Females</b>						
<b>Post-H.S. earnings and employment</b>	<b>H.S. grads</b>	<b>H.S. grad + failed course</b>	<b>High school grads</b>		<b>H.S. grad + failed course</b>	
			<i>Enrolled college</i>	<i>No college</i>	<i>Enrolled college</i>	<i>No college</i>
1 yr. after graduation	<b>849.72</b>	27.69	493.53	2.30	-772.88	366.80
2 yrs. after graduation	<i>372.17</i>	-632.35	-20.06	-275.00	-1886.48	-185.26
3 yrs. after graduation	<b>-1912.78</b>	-1909.02	<b>-3841.14</b>	-174.82	<b>-5100.60</b>	1874.00
4 yrs. after graduation	-582.44	-1397.62	-2984.85	154.74	-3743.74	351.37
<b>Males</b>						
<b>Post-H.S. earnings and employment</b>	<b>H.S. grads</b>	<b>H.S. grad + failed course</b>	<b>High school grads</b>		<b>H.S. grad + failed course</b>	
			<i>Enrolled college</i>	<i>No college</i>	<i>Enrolled college</i>	<i>No college</i>
1 yr. after graduation	-14.05	-1040.88	308.85	-1011.89	-343.03	-1439.79
2 yrs. after graduation	<i>-14.97</i>	-642.10	<i>-20.06</i>	-1508.32	-843.67	-548.98
3 yrs. after graduation	-1295.98	-1805.03	-3422.73	-528.21	-3434.39	-815.72
4 yrs. after graduation	-4008.74	-3793.90	-4942.69	-3327.59	-5414.80	-2919.00

Notes: Coefficient estimates in boldface are statistically significant at  $\alpha=0.05$ . 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.

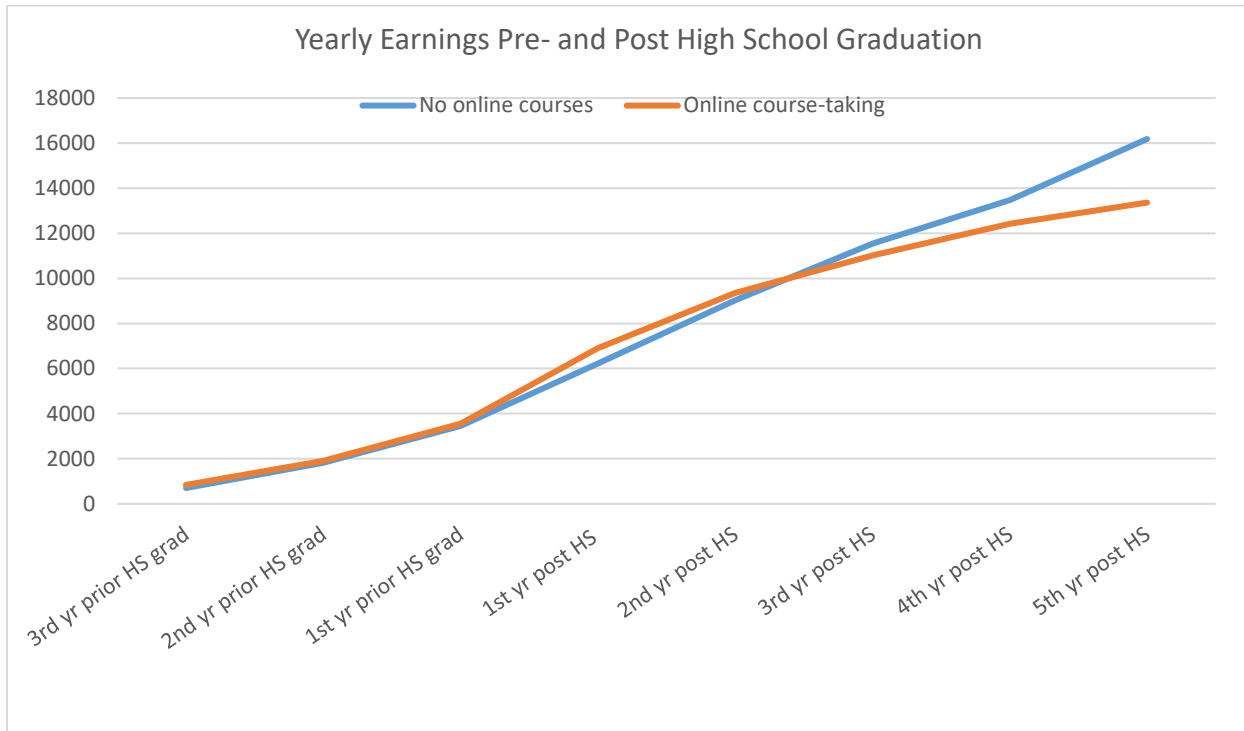
<b>Table 4: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings</b>			
<i>Adjusting for missing data</i>			
	<b>High school graduates (n=11,714)</b>		
<b>Post-H.S. earnings and employment</b>	All H.S. grads	<i>Enrolled college</i>	<i>No college</i>
1 yr. after graduation	127.02	158.28	-462.20
2 yrs. after graduation	<i>108.85</i>	<i>215.78</i>	-468.27
3 yrs. after graduation	<b>-446.73</b>	<b>-766.57</b>	-348.13
4 yrs. after graduation	-177.31	-427.59	-135.94
	<b>H.S. graduate + failed course (n=6,322)</b>		
Post-H.S. earnings and employment	All H.S. grad + failed course	<i>Enrolled college</i>	<i>No college</i>
1 yr. after graduation	-345.09	-456.70	-358.74
2 yrs. after graduation	-316.31	-450.78	-383.48
3 yrs. after graduation	<b>-723.92</b>	<b>-1562.01</b>	-119.03
4 yrs. after graduation	-224.63	-567.60	-98.90

Notes: Coefficient estimates in boldface are statistically significant at  $\alpha=0.05$ . 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 1: Descriptive Trends of Student Quarterly Earnings Prior to High school Graduation, by Online Course-taking in High School**

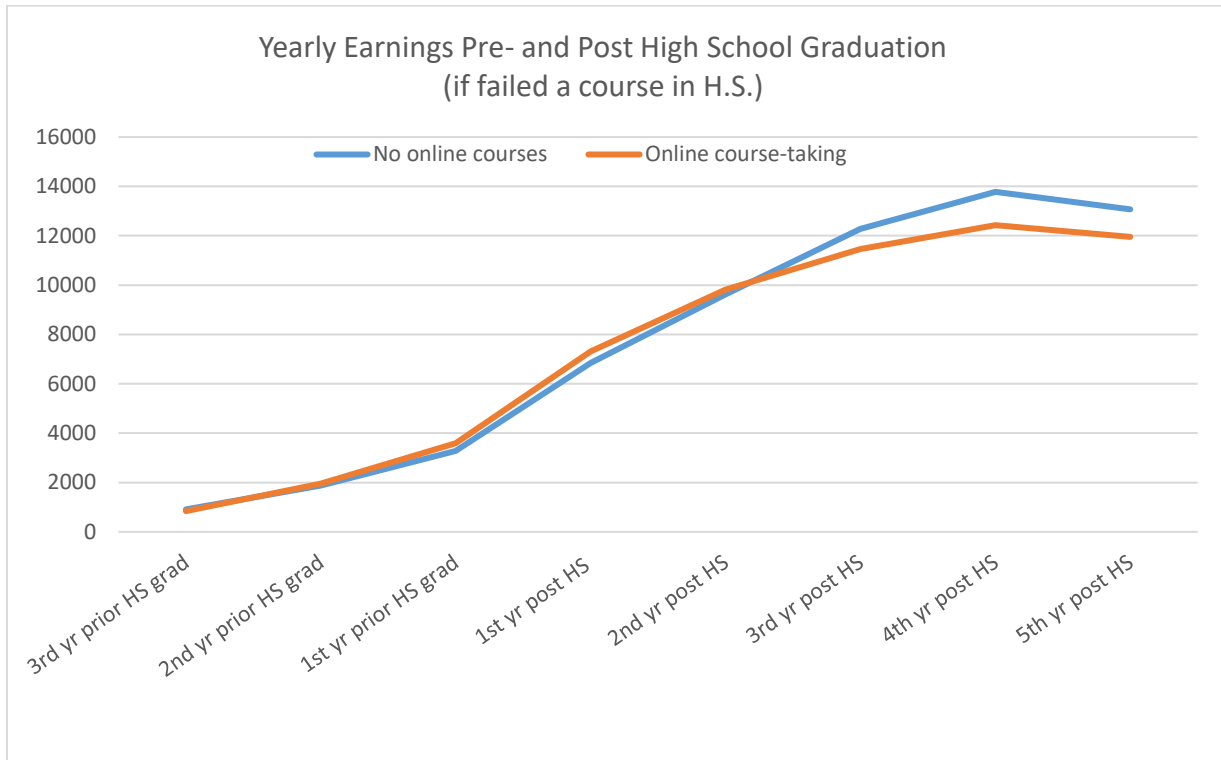


**Figure 2: Descriptive Trends of Student Annual Earnings Before and After High school Graduation, by Online Course-taking**

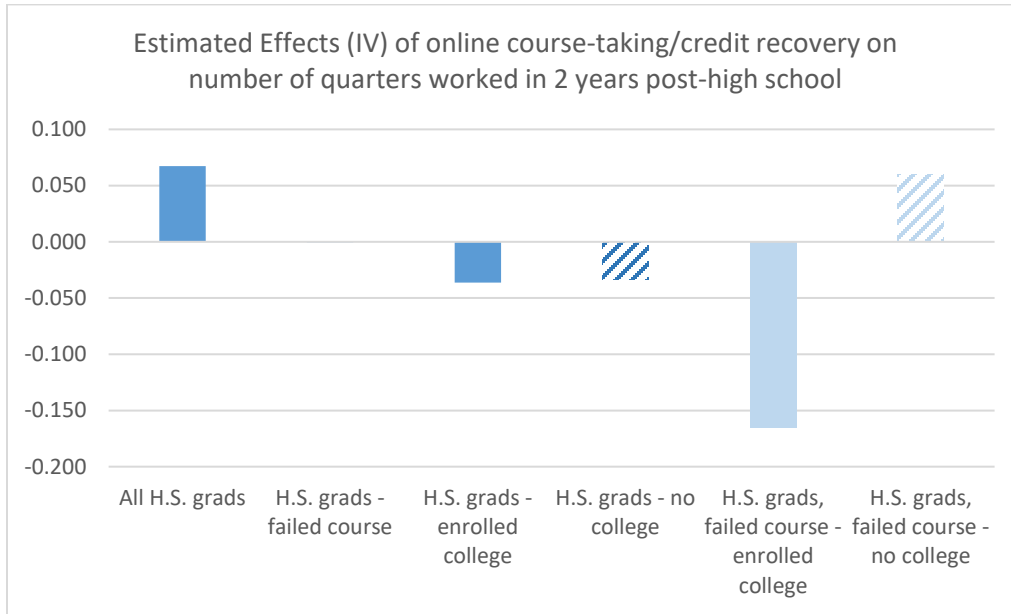




**Figure 3: Descriptive Trends of Student Annual Earnings Before and After High school Graduation, by Online Course-taking, for Students Who Failed a Course in High School**

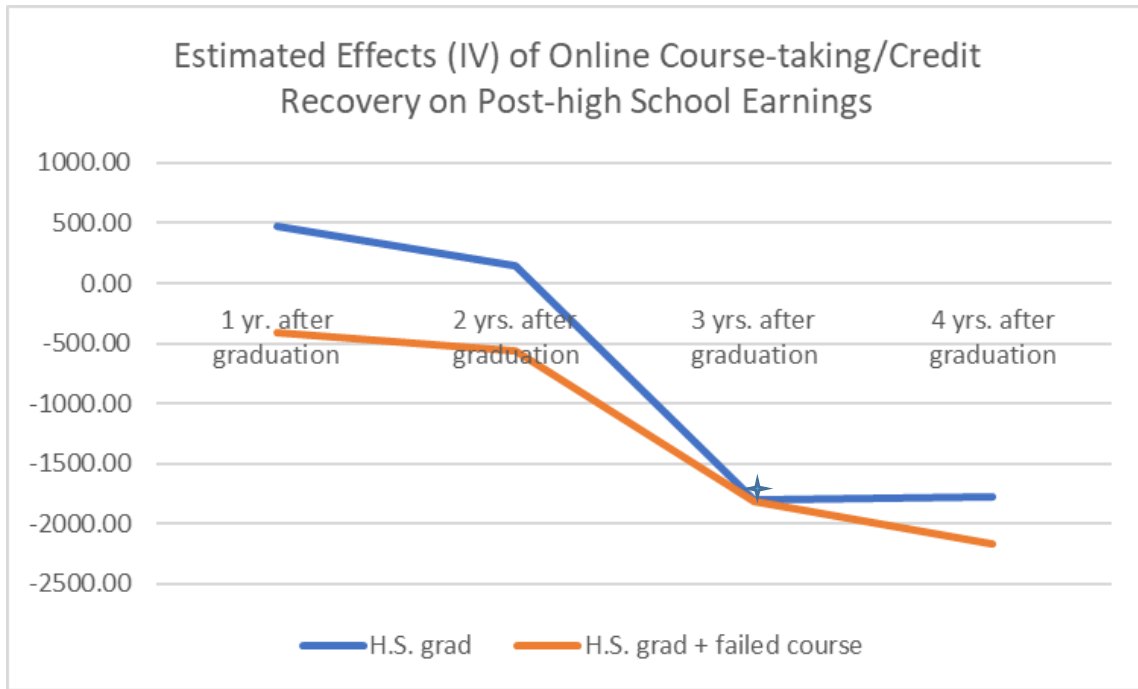


**Figure 4: Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Employment for High school Graduates**



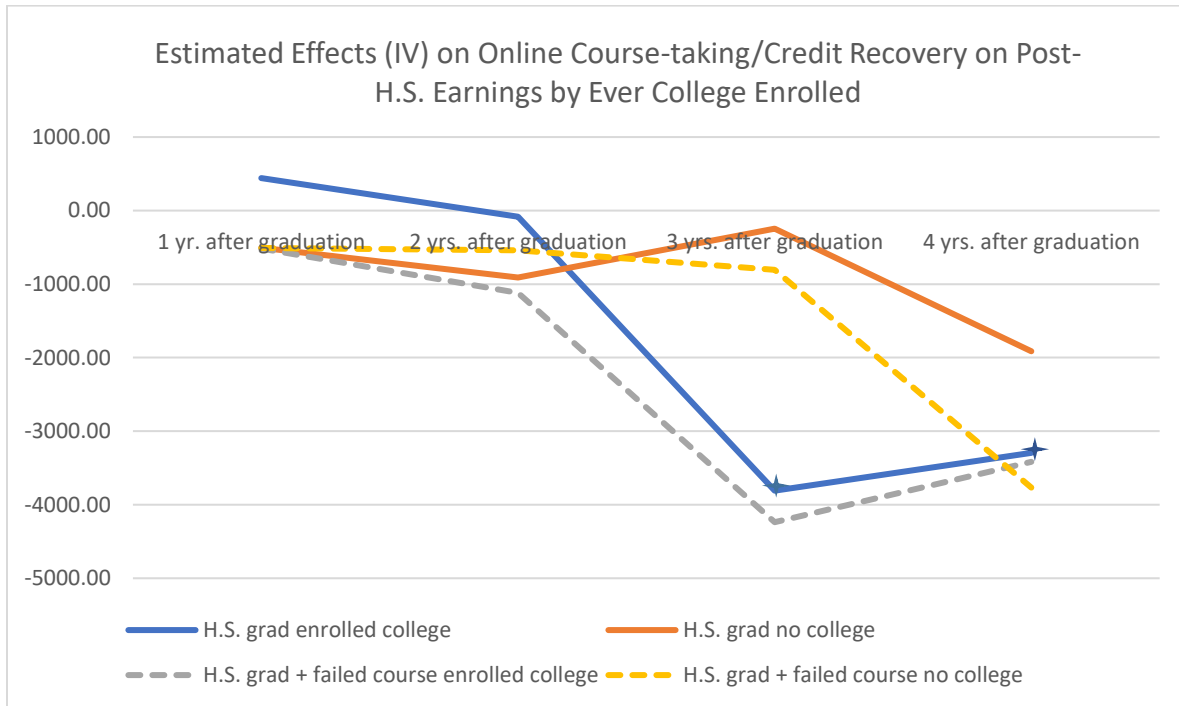
See Table 2 for a tabular summary of these results and notes on the estimation.

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



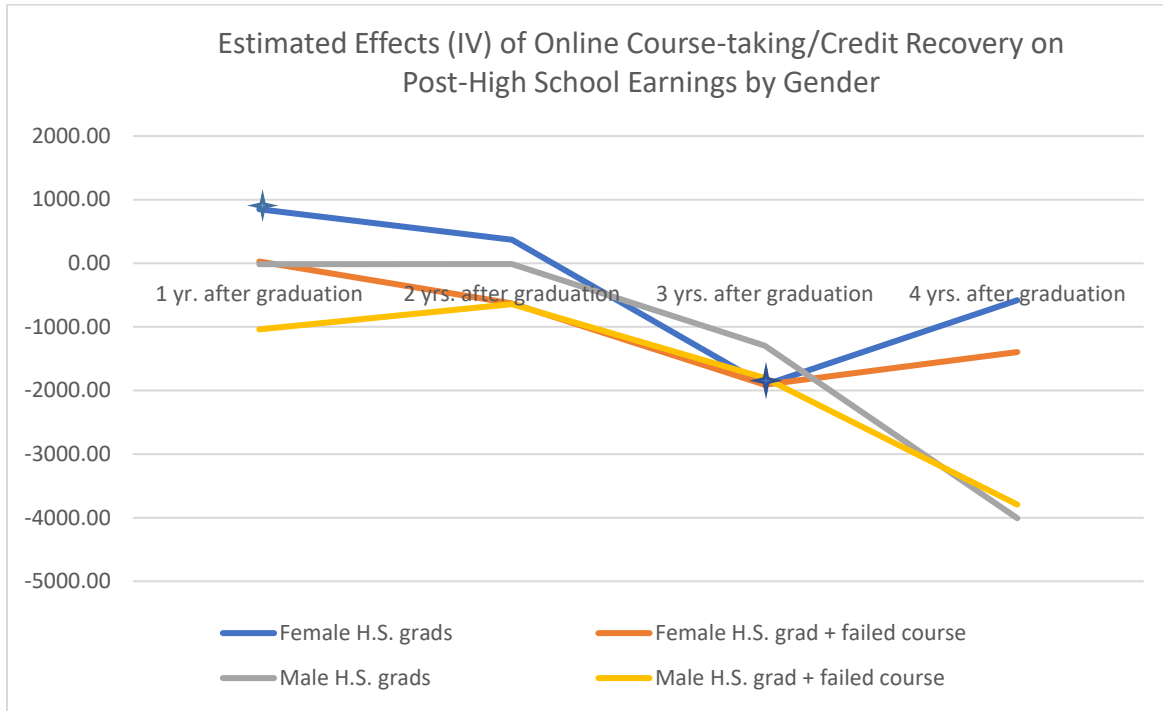
See Table 2 for a tabular summary of these results and notes on the estimation. The symbol, \*, indicates a statistically significant coefficient estimate.

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



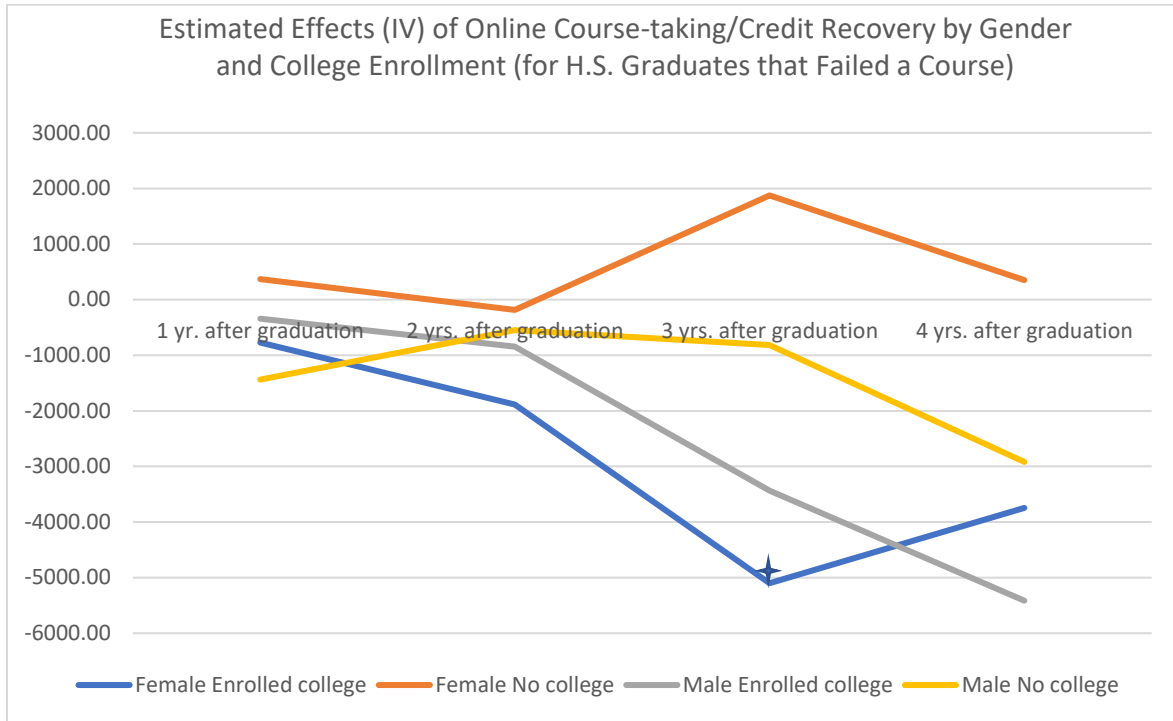
See Table 2 for a tabular summary of these results and notes on the estimation. The symbol, ✦, indicates a statistically significant coefficient estimate.

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



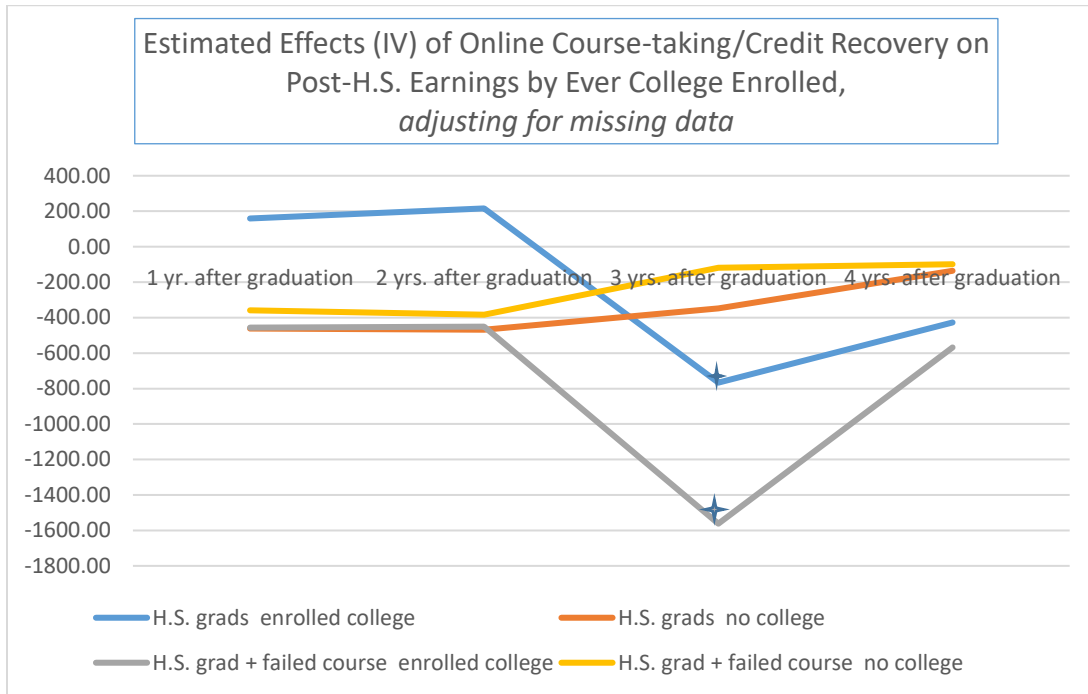
See Table 3 for a tabular summary of these results and notes on the estimation. The symbol, , indicates a statistically significant coefficient estimate.

**Figure 8: Instrumental Variables Regression Estimates by Gender of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates Who Failed a Course in High School**



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

**Figure 9 Instrumental Variables Regression Estimates of Online Credit Recovery Effects on Post-High School Earnings for High School Graduates by College Enrollment, Adjusting for Missing Data**



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

## Appendix A: First-stage Instrumental Variables Model Results

First-stage (IV) model: Predicting participation in online course-taking						
<i>Student characteristics</i>	High school graduates			H.S. graduates - failed a course		
	Female	-0.005	0.009	0.557	-0.012	0.013
Asian	-0.020	0.018	0.272	-0.065	0.038	0.091
White	<b>-0.048</b>	0.014	0.001	<b>-0.061</b>	0.024	0.011
Hispanic	<b>-0.050</b>	0.013	0.000	<b>-0.054</b>	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	<b>-0.046</b>	0.017	0.006
Student w/disabilities	0.005	0.013	0.693	-0.001	0.018	0.944
Percent absent	<b>0.321</b>	0.044	0.000	<b>0.210</b>	0.051	0.000
GPA	<b>-0.111</b>	0.008	0.000	<b>-0.141</b>	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	<b>0.114</b>	0.013	0.000		(omitted)	
Year graduated - 2012	<b>-0.326</b>	0.046	0.000	<b>-0.340</b>	0.050	0.000
Year graduated - 2013	<b>-0.204</b>	0.012	0.000	<b>-0.269</b>	0.019	0.000
Year graduated - 2014	<b>-0.075</b>	0.012	0.000	<b>-0.089</b>	0.019	0.000
Year graduated - 2015	<b>0.037</b>	0.011	0.001	<b>0.054</b>	0.016	0.001
<i>School characteristics</i>						
% in online courses	<b>1.152</b>	0.032	0.000	<b>1.228</b>	0.048	0.000
% Black	<b>-0.154</b>	0.029	0.000	<b>-0.340</b>	0.042	0.000
% English learners	-0.039	0.092	0.674	<b>-0.328</b>	0.119	0.006
% Free lunch	<b>0.301</b>	0.078	0.000	<b>0.647</b>	0.118	0.000
% Special needs	<b>0.596</b>	0.136	0.000	<b>0.533</b>	0.184	0.004
% in advanced courses	<b>-0.099</b>	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	<b>-0.227</b>	0.070	0.001	-0.241	0.094	0.010
% in CTE	<b>-0.125</b>	0.015	0.000	<b>-0.100</b>	0.020	0.000
Alternative school	<b>-0.126</b>	0.027	0.000	<b>-0.166</b>	0.033	0.000
Charter school	<b>-0.128</b>	0.030	0.000	<b>-0.322</b>	0.046	0.000
Citywide specialty school	<b>0.094</b>	0.015	0.000	<b>0.090</b>	0.019	0.000
Constant	<b>0.262</b>	0.068	0.000	0.293	0.102	0.004
<i>Adjusted R-squared</i>	41.68%			32.24%		
<i>Model F value</i>	392			134		

Notes: Coefficient estimates in boldface are statistically significant at  $\alpha=0.05$ . 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 Estimates of Online Credit Recovery Effects on Post-High School Earnings					
<i>Treatment=Took courses online in high school</i>					
Post-H.S. earnings and employment		High school grads		H.S. grad + failed course	
		<i>Enrolled</i>	<i>No college</i>	<i>Enrolled</i>	<i>No college</i>
Earnings 1 yr. post H.S.	8,835	125.40	<b>717.10</b>	206.24	<b>687.97</b>
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

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

