Online Learning as a Remedy for Course Failure: An Assessment

of Credit Recovery as an Intervention to Earn Credits and Graduate from High School

By

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To my former students in Chicago, whose struggles and triumphs inspired this dissertation

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INTRODUCTION

While prior literature has focused on potential reasons why students do or do not graduate from high school, very few studies evaluate interventions that specifically target a common predictor of not graduating from high school: the failure of required courses. This study works to strengthen this literature by addressing an increasingly popular tool schools are using to help students regain credit they lost through course failure: credit recovery courses. Credit recovery refers to online courses that students take after failing a class the first time they enroll in the course. While online learning was originally designed for students interested in accelerated or enrichment activities, credit recovery courses are specifically designed for at-risk high school students whose motivations and skill levels are likely different from the intended online learner. Furthermore, the increasing popularity of credit recovery is clear, but the actual enrollment in credit recovery and the effectiveness thereof are unknown. Prior to credit recovery, students who failed a course simply repeated it in full, either in summer school, after school, or during the school year. While the efficacy of these traditional interventions is unclear, the comparison of the effectiveness of traditional approaches versus credit recovery in helping students regain course credit and graduate from high school has only rarely been assessed.

This dissertation aims to address these gaps in the literature on credit recovery through three separate essays, each taking a different approach to credit recovery. In order to gain a baseline understanding of credit recovery enrollment and efficacy, the first essay compares enrollment in credit recovery to enrollment in repeating a course traditionally for students who fail courses. This first essay answers baseline questions about enrollment numbers, changes over time, the type of student who enrolls in credit recovery, and the type of school that is more likely to enroll students in credit recovery. This essay also investigates the efficacy of credit recovery as an intervention to regain course credit lost through course failure.

While the first essay relies on descriptive analysis, the second essay makes claims about the causal effect of credit recovery by using quasi-experimental methods. The second essay investigates whether students who enroll in credit recovery are more likely to graduate and less likely to drop out of high school compared to other students who fail courses but repeat the course in full. While it is important as a baseline measure that students earn course credits from credit recovery courses, if such students are not more likely to graduate from high school, then credit recovery cannot be deemed an effective intervention for its intended distal outcome. Using fixed effects and a matching approach, this essay integrates a host of robustness checks to attempt to find the causal effect of credit recovery on the likelihood of high school graduation.

The first two essays are mostly focused on the student-level correlates and effects of credit recovery, especially comparing credit recovery students to students repeating courses traditionally. However, credit recovery courses can have associated externalities that go beyond the individual student effects. Implementing credit recovery courses could have an effect on the climate of a school, since it changes the traditional paradigms of how schools are responding to course failure. While repeating a course can naturally feel like a burden to a student, credit recovery—a time during the school day with almost unfettered access to the internet and time away from classrooms and teachers—might seem like a reward to some. This kind of positive reinforcement of negative behavior could have negative effects on all areas of school performance. Conversely, credit recovery could only positively affect school performance by increasing graduation rates while avoiding the reinforcement of negative behavior. The third essay uses a comparative interrupted time series approach to address these policy-relevant questions by answering questions about the effects of credit recovery implementation on school-level outcomes.

This dissertation represents an important step in understanding the underlying patterns, effectiveness, and intended and unintended consequences of credit recovery. While practitioners in schools are incentivized by unforgiving accountability targets to implement quick and easy interventions like credit recovery, it is important to understand whether this particular intervention is meeting its intended purpose, and whether it comes with unexpected costs to the school's performance. Using highly generalizable data from all non-charter public schools in the state of North Carolina, this dissertation provides valuable information that will increase knowledge about credit recovery to help practitioners make informed decisions.

CHAPTER I

CREDIT RECOVERY AND REPEATING A COURSE FOR CREDIT: WHICH STUDENTS ENROLL IN EACH OPTION AND WHAT ARE THE CONSEQUENCES OF THIS ASSIGNMENT?

Introduction

Recently, high schools have been subject to federal accountability pressures to increase graduation rates ("No Child Left Behind High School Graduation Rate Non-Regulatory Guidance," 2008; "Overview Information; Race to the Top Fund; Notice Inviting Applications for New Awards for Fiscal Year 2010; Notice," 2010). At the same time, high school graduation rates have hit a historic high, setting new annual records ("Common Core of Data (CCD)," n.d.; "National Center for Education Statistics," n.d.; "U.S. High School Graduation Rate Hits New Record High | U.S. Department of Education," n.d.). One possible explanation is credit recovery courses. Credit recovery, a recent addition to the possible remedies for course failure, refers to online courses specifically designed for students who have previously failed a traditional (i.e., face-to-face) version of that course. Since course failure is a strong predictor of failing to graduate from high school (see Allensworth & Easton, 2005; Bowers, 2010; Mac Iver & Messel, 2013), credit recovery offers students who fail courses the ability to regain those credits in a way that was not available to them before. Traditionally, students have addressed course failure by retaking the course in full, taking the course after school (e.g., in a twilight program), or taking the class in summer school. However, credit recovery is arguably a more efficient way to earn course credit for failed classes because of the flexible online format and the ability to complete multiple courses within the same timeframe as retaking one full course.

Several recent studies strongly suggest that credit recovery has become a staple offering in high schools around the U.S, apparently dominating online course offerings. A nationwide survey in the 2009-10 school year indicated that approximately 55 percent of school districts enrolled students in distance education courses, with 62 percent—over 1.1 million enrollments—for credit recovery (Queen & Lewis, 2011). When North Carolina Virtual Public Schools (NCVPS), now the second largest statewide virtual school in the U.S. (Murin, Powell, Roberts, & Patrick, 2015), began offering online courses in summer 2007, 78 percent of enrollments were for students in credit recovery courses (Oliver, Osborne, Patel, & Kleiman, 2009). In a 2012-13 survey of public high schools in Iowa and Wisconsin, credit recovery was their top reason for offering online courses (Clements, Stafford, Pazzaglia, & Jacobs, 2015). From a 2012-13 survey of public high schools in the Albany, New York, area, about 60 percent of schools offered online courses, and about three quarters of students enrolled in online courses were enrolled in a credit recovery course; 82 percent of schools reported that online courses for credit recovery was a very important reason for having online courses (Clements, Zweig, & Pazzaglia, 2015). As shown in Table 1, overall estimates of enrollment or offerings of credit recovery are highly disparate, depending on the study. Reports on schools in Iowa, Wisconsin, North Carolina, and nationwide indicate credit recovery as an option at three quarters of schools. A study of schools in the Albany, New York, area (the Capital Region) indicates credit recovery as an option at about half of schools. Longitudinal evidence from the Florida Virtual School indicates that credit recovery enrollment is growing quickly over time, from 259 enrollments in 2007-08, to 4,063 enrollments in 2010-11.

Evidence on distance learning in higher education suggests that online learning might not be an effective tool for student learning, especially for high-risk students who may need extra support and structure (Xu & Jaggars, 2011). Only two available studies have assessed the effectiveness of credit recovery. The first, using a randomized control trial design, found that students in Algebra I summer credit recovery courses in Chicago were less likely to receive course credit and received lower posttest scores than students assigned to a traditional face-to-face summer school course (Heppen et al., 2016). The second study included students who failed core courses, comparing those who enrolled in the state-run North Carolina Virtual Public School's credit recovery courses to students who made up the credit by repeating the full course during the school year, or taking it in summer school. Using ordinary least squares and logistic regression, this study found that credit recovery students had lower scores and were less likely to pass an end-of-course exam. Credit recovery students were less likely to graduate from high school, but were more likely to graduate from high school on time (i.e., in four years) (Stallings et al., 2016).

Despite limited evidence available on the proliferation and effects of credit recovery, many major media outlets like *Education Week* and *NPR* have published pieces excoriating schools and districts for giving students the option to take what the journalists assume to be low-quality credit recovery courses that are used as an easy way to graduate more students (Burke, Chapman, & Monahan, 2013; Gardner, 2016; Turner, 2015). These media sources accuse schools and districts of funneling at-risk students into credit recovery courses that are low-quality, and wherein students gain little from the course besides the credit itself. However, we actually know little about these courses, the students who take them, and the schools that offer them.

This study focuses on the prevalence, distribution, and variation in credit recovery course-taking at both the student and school level. The findings represent an important first step in investigating whether credit recovery is being widely used enough to warrant future study through experimental and quasi-experimental designs. Course failure is not a new problem, but credit recovery offers a new solution. Knowing the popularity of credit recovery compared to other options for addressing course failure is an important step toward understanding how schools are using credit recovery courses. To address these areas, I will assess the following research questions:

1. When students fail a core course required for high school graduation, how often do they repeat the course for credit, take the course through credit recovery, do neither, or do both?
2. To what extent do the ways in which a student addresses course failure vary across schools and change over time?

As noted above, journalists and researchers have raised many concerns about credit recovery, and I will address several areas where potential issues with credit recovery might arise. With no information pointing to the efficacy of credit recovery, there is a natural concern that the most vulnerable student populations are disproportionately exposed to credit recovery courses. It is unknown whether credit recovery is being used with mostly marginalized student populations or in under-resourced school settings. Schools that traditionally struggle to graduate students might be more likely to implement a program like credit recovery, which offers a low-cost way for more students to earn credits in less time (see below for more information on costs and time associated with credit recovery). In order to assess whether or not course-taking is associated with certain student or school characteristics, I will address the following research question:

3. To what extent does a student's enrollment in credit recovery or repeating a course for credit relate to the students' characteristics or the characteristics of the school they attend?

Another natural concern about credit recovery is whether or not students are actually gaining course credit if they take a credit recovery course, and how those course credit earning rates compare to the traditional method of repeating a course for credit:

4. To what extent is repeating a course for credit, credit recovery, neither, or both associated with ultimately gaining credit for the course?

If credit recovery has become an especially popular option at schools, it is possible that repeating a course for credit could become increasingly obsolete. Credit recovery crowding out other options available to students who fail courses could have major ramifications for student learning if credit recovery courses are systematically of lower quality than traditional courses. In order to assess whether or not this is occurring, I will address the following research question:

5. To what degree are credit recovery rates increasing at the school-level over time at a rate that is high enough to lead to a crowding out of other options for addressing course failure?

Literature Review on Credit Recovery

As noted above, in many schools, credit recovery has become a common remedy for course failure in an effort to reduce the risk of dropping out and failing to graduate. Traditionally, students who failed courses had two options: repeat the course in a subsequent semester, or take a version of the course specifically designed for students who had failed, which is taught in a traditional classroom setting, but offered after school or over the summer. Online learning through credit recovery provides an alternative for gaining credits from previously failed courses and offers several appealing attributes, which can include flexibility, relatively easy expansion, a lack of interference with students' carrying a normal course load, and lower costs for delivery. Schools have the option of offering credit recovery at any time in any location, thus making it simple for students to recover course credit on their own schedules, though schools can choose to offer credit recovery during the school day. The other methods of gaining course credit require a certified teacher as the instructor, leading to potentially higher costs and less flexibility than a self-paced online course. Unfortunately, research has not devoted much attention to the popularity of credit recovery, but a few studies have been conducted on the costs, implementation, and experiences of those involved with it.

Expansion of the number of students enrolled in credit recovery comes at some cost to the school district; however, this cost is considered to be less than the cost of hiring more teachers to teach additional students (Murin et al., 2015). Some public providers of online credit recovery courses (i.e., state or district-run courses) do not charge schools to enroll students in courses, so costs are potentially limited to the necessary technology (i.e., computers and internet access). However, many online courses are partially taught by an online instructor, include an in-room monitor to supervise the credit recovery students, and/or have a monitor who is a certified teacher, all of which add substantial costs. Credit recovery course flexibility can also range from the traditional constraints of being offered within the school day as a part of the student's course schedule (and most likely with an in-class monitor or teachers), to the extreme fluidity of being available for students to complete at their own pace anytime, anywhere they wish to work on the course (Ingerham, 2012; Levy, 2011; Murin et al., 2015; Oliver & Kellogg, 2015). We know little about the extent to which these two credit recovery formats are utilized. A 2012-13 survey of a stratified random sample of schools in Iowa and Wisconsin indicated that most schools enrolled students in synchronous online courses, for both credit recovery and non-credit recovery, where the students had the opportunity to communicate directly with an online teacher, and schools assigned an onsite monitor to supervise students in online courses (Clements, Stafford, et al., 2015).

Credit recovery can be offered through statewide virtual schools, district virtual schools, or private providers. As of 2008, 40 states had state-run online course providers, which are designed to offer online courses to students enrolled in traditional brick-and-mortar schools, thus supplementing the more traditional face-to-face offerings (Watson, Gemin, & Ryan, 2008). The largest state-run virtual course provider is in Florida, and enrolled over 377,000 students in 2013-14, followed by NCVPS, which enrolled about 105,000 students in online courses the same year. While these enrollment numbers include credit recovery and other online learners, all courses offered through Florida Virtual School have a version that can be taken for credit recovery. Many large school districts also have their own, in-house providers of online courses, which function in the same capacity as the state-run virtual schools (Watson, Gemin, & Ryan, 2008). Another significant provider of credit recovery courses are for-profit companies that contract to schools and districts to provide specific courses to the schools (Murin et al., 2015). For instance, Apex Learning is a privately-held company founded and staffed by former executives at Apple and Microsoft, and claims on their website boast that their online course enrollments in 2014-15, including credit recovery, reached over two million (“Apex Learning—About Us,” n.d.). More detailed information on the widespread use of private providers of credit recovery courses is difficult to find. As described in a recent report on credit recovery in North Carolina public schools, these private providers do not readily share information, such as the schools and districts with whom they have contracts, and overall enrollment numbers. After interviewing representatives from seven private credit recovery providers in North Carolina, the report's author had little detailed information, but confirmed with the vendors that at least 87 percent of districts in North Carolina had a contract with one of the seven interviewed providers (Stallings et al., 2016).

Additionally, little is known about the content, pedagogical approaches, and assessments in credit recovery courses. In an article on NCVPS deployment in summer 2007, the authors indicate that all courses were aligned to the Southern Region Education Board's e-learning standards, which were later adopted by the North American Council for Online Learning as the National Standards for Quality Online Teaching (Oliver et al., 2009). This study also includes information from a survey of all online instructors and students who enrolled in an online course through NCVPS that summer, separating both groups into those involved in an accelerated course and those involved in a credit recovery course. Teachers of credit recovery courses rated the quality of resource materials as significantly lower than those submitted by teachers of accelerated courses. The majority of credit recovery students did not have a clear idea of how their work was evaluated, and often did not receive timely feedback on assignments (Oliver et al., 2009). In an attempt to understand the content of credit recovery courses, a follow-up survey of teachers of credit recovery courses was conducted in a more recent summer (actual year of the survey was not noted in the paper), with teachers indicating that credit recovery courses are mastery-based, included new teaching strategies, and utilized interactive web tools. The online instructors rarely encouraged collaborative assignments, provided little prompting for peer-to-peer learning, and offered little use of hands-on or authentic projects (Oliver & Kellogg, 2015). In an ethnographic study of NCVPS Algebra I credit recovery students, Ingerham (2012) found that the majority of students spent a significant amount of time on other, unrelated websites (mostly YouTube) during the class period they were assigned to work on their credit recovery curriculum. In contrast to this study, Levy's (2011) ethnographic study of migrant students in Texas indicated that those students were given access to a personal laptop for a year, which they could use to complete multiple credit recovery courses. Students could work on their credit recovery courses offered through NovaNET (Pearson) any time after 5 p.m. on weekdays, and throughout the weekend. The average student in that program earned three-and-a-half course credits through credit recovery courses.

Background on Credit Recovery in North Carolina Public Schools

Since 2007, the NCVPS has provided sufficient online courses to make it the second largest state-run virtual provider of online courses, as noted above. The North Carolina General Assembly created NCVPS in 2002, originally to assist with homebound student instruction, to reduce class sizes, and to offer advanced courses to rural students whose home schools had limited course offerings (Banks, Bodkin, & Heissel, 2011). As of the 2016-17 school year, NCVPS offered 14 credit recovery courses. Students from all 115 North Carolina school districts and most charter high schools take NCVPS courses, and schools are charged between $235 and $438 per course enrollment, depending on the time of year the course is offered (i.e., summer, year-long, or semester-length). All courses have an online instructor ("North Carolina Virtual Public School," n.d.). Many districts and schools in North Carolina also contract to private credit recovery providers, including Apex, Edmemtum, PLATO, and Odysseyware.

Nevertheless, it is unclear and likely highly varied how students are enrolled in credit recovery. In order to gain a clearer picture of the credit recovery assignment or enrollment process, I conducted interviews with district and school-based officials in several school districts in North Carolina. Based on these interviews, credit recovery assignment varies depending on district/school policies. One policy that came up more than once is one that only allows a student to take a credit recovery course if their grade in the course they failed was between a 50 and 59 percent (60 percent and above is passing). Another district reported allowing only students who failed a course due to excessive absences to take credit recovery. In both of these districts, however, students can appeal their assignment to repeating a course for credit such that credit recovery is not strictly limited to students who meet the district requirements. Thus, the districts have official appeals processes that allow students some autonomy in their course assignment. In at least one school site, students can decide whether or not to take a credit recovery course, although teachers can also be part of this decision-making process (and both parties can change their mind mid-semester). The ways credit recovery courses are supervised also varies by district. One district reported having a certified teacher in every credit recovery classroom, while other districts have an attending employee who is similar to a teacher's aide. In those school districts, the person supervising credit recovery only needs a high school diploma for the position. While I did not speak to a district that has an unsupervised credit recovery model (i.e., students are expected to complete their credit recovery course outside of school hours), I am unaware of any state requirement or regulation that would prohibit or discourage this practice.

The North Carolina State Board of Education has adopted several official policies on credit recovery courses that apply to all courses regardless of whether they are offered through NCVPS or a private provider. Officially, credit recovery indicates instruction that is less than the entirety of *The Standard Course of Study* (i.e., the official state-wide standards for required academic courses) for that course, instead focusing on problem areas in the student's learning.

Credit recovery courses are offered as pass/fail with no grades that will factor into a student's GPA. If students wish to earn a new grade for a course, then they must repeat the entire course, a process officially termed *repeating a course for credit*. The length of credit recovery courses is based on the amount of time it takes a student to master the content, and students are not to be limited in the number of credit recovery courses they are allowed to take. Students take the official state end-of-course exam upon completion of the credit recovery course when applicable (Garland, Brown, & Beamon, 2010).

While these are the official regulations governing credit recovery, the state has not indicated how often students are enrolling in credit recovery courses or any outcomes of credit recovery students, such as the rates at which credit recovery students earn course credits. This study aims to fill this information gap by exploring the prevalence of credit recovery across the state. Additionally, it investigates which students are more likely to take credit recovery based on their characteristics and the characteristics of their schools.

Methods

Data and Sample

The data from this project includes student-level records from an administrative database, including all students enrolled in public schools in North Carolina. This administrative database is maintained by the Education Policy Initiative at the University of North Carolina at Chapel Hill (EPIC), and includes longitudinal information on students, their schools, and their teachers. Student-course roster files and student grade records are essential data files for this project, as these files identify students who have enrolled in credit recovery or who are repeating a course for credit. These files also identify each course (e.g., Math I, English II) in which a student is enrolled.

The unit of analysis is the student-course. Each record represents one course that a student has failed anytime in high school (i.e., the number of records for each student is equal to the number of unique courses a student has failed). The sample is restricted to high school student-course records for only core, required courses (see "High School Graduation Requirements," n.d.)[1] that a student failed anytime in high school (i.e., 9^{th}-12^{th} grade). The sample includes only student-course records for courses that a student failed between the 2012-13 and 2016-17 school years. In order to investigate student and school characteristics associated with credit recovery enrollment or repeating a course for credit, I compiled several data files with information on demographics, academic performance, and attendance at both the student and school level.

This study focuses on core, required courses for two reasons. First, if credit recovery courses were specifically implemented in order to raise graduation rates (as was explained in the introduction), then, theoretically, the impact of offering credit recovery would be concentrated among the courses that address graduation requirements. The second reason is practical. Students enroll in thousands of courses annually, and the credit recovery identification process (explicated below) involves identifying either all of the courses or a well-defined subset of those courses. Identifying all courses in which students enroll regardless of their utility in determining whether or not a student graduates from high school would be extremely time-consuming, and possibly subject to greater error due to the number of courses with numbering or title changes. Since

[1] Regardless of year or track, students are required to complete four years of English, at least three math courses, Biology along with at least one other science course, and at least two social studies courses. Go to http://www.ncpublicschools.org/docs/curriculum/home/graduationrequirements.pdf for more information.

credit recovery is first and foremost an intervention to obtain credit and stay on track for high school graduation, focusing on the subset of required core courses makes the process manageable and provides important evidence related to the overall goals for credit recovery.

Measures

The key measure to address the research questions of this study is how students responded to course failure: through repeating a course for credit, credit recovery, neither, or both. While students might repeat a course for credit during the school year, over the summer, or after school, this study does not differentiate between these options due to data limitations. The first task is to identify which students failed a core, required course using students' grades and course roster information. Repeating a course for credit is defined as failing a course and repeating the course for credit with no indication that, when they repeated the course, they did so online. Identifying whether a student's course is credit recovery is based on several source variables. A student can both repeat a course for credit and take credit recovery, because they might have attempted one of those options and failed the course a second time. Because no single variable or procedure can identify all credit recovery courses, I follow a multistep process to identify credit recovery courses and students enrolled in those courses. Students in credit recovery previously failed a course, and then retook the course online, as indicated through course codes and course titles. Credit recovery courses are also identified through grades, where a grade of a "pass" or "fail" indicated a credit recovery course because only credit recovery courses are graded on a pass/fail basis, according to state-level rules.

In order to answer the third research question about the ways in which student and school characteristics influence how students address course failure, the dataset includes a rich set of covariates. Student demographic and other student-level information is available on an annual basis and includes student race/ethnicity, gender, whether the student is or was designated as Limited English Proficient (LEP), whether the student is gifted, whether the student is classified as economically disadvantaged, and whether the student is enrolled in special education services. These covariates will indicate if certain types of students—particularly students at risk of not graduating, who, based on the disparity in graduation rates, tend to be low-income and from a racial minority—are more or less likely to be in credit recovery. These same covariates are available at the school-level for the percentage of students in the school in each category. Financial information is available at the school-level, indicating different financial resources available to the school. Financial information will allow for the comparison between a school's financial resources and credit recovery course taking. In high school, students take end-of-course exams in Math I, Biology, and English II. The lagged proficiency rates on these exams at the school level will be included to examine whether school performance in the previous school year is associated with how students address course failure. The lagged high school graduation rate will also be in the models to assess whether schools respond to the graduation rate through placing more or less students in credit recovery. The last lagged variable will be the course failure rate. The course failure rate indicates the percentage of first-time, core course enrollments that result in a failure. Schools might respond to higher course failure rates by increasing their credit recovery enrollment the following school year, which will be tested by including this variable. Other school-level variables that will be included are enrollment, teacher experience levels, the percentage of teachers with National Board Certification, suspension rates, and the number of violent acts per 100 students. Covariates are also included, indicating the student's middle school academic performance, including average scores on the end-of-grade tests given in eighth grade, to see whether different indicators of being at-risk from middle school are associated with how a student addresses course failure in high school.

The outcome for the fourth research question is whether or not students gain credit for a course that they previously failed. A student has gained credit for such a course if the credit recovery course or the course in which they are observed to be repeating for credit is associated with a numeric or letter grade above failing, or a grade of "pass."

Variables measuring the prevalence of credit recovery in a school are necessary to answer the second and fifth research questions. This measure indicates the percentage of failed student-course records that fall into one of four categories: did not repeat or take credit recovery, took credit recovery only, repeated the course only, repeated the course and took credit recovery.

Empirical Framework

The first research question for the study asks how often students who fail courses repeat a course for credit, take credit recovery, do both, or do not appear to address their course failure. The second research question asks how and whether or not students address course failure varies across schools and has changed over time. In order to answer these two questions, descriptive tables, bar charts, and trend lines will show enrollment rates in credit recovery or repeating courses for credit for failed students both overall and over time.

The third research question asks whether the decision between repeating a course for credit or credit recovery is related to student or school characteristics. A multilevel logistic regression model will answer this research question. The model is logistic because the option of repeating a course for credit or taking credit recovery is a binary outcome.[2] The model is multilevel because student-course records are clustered within students, and students are clustered within schools, resulting in three levels.[3,4] The covariates listed in the Measures section will be in the model at the student- or school-level. The covariates at the course-level will be indicators of the core course subject (i.e., Math, Science, Social Studies, or English). The analysis will explore which course-level, student-level, and school-level covariates are predictive of enrolling in credit recovery as opposed to repeating a course for credit. I will explore the resulting coefficients from the model both for their statistical as well as practical significance to see if there is any indication that credit recovery is systematically being used for some students or in some settings over others.

The fourth research question asks if repeating a course for credit, taking credit recovery, neither, or both is associated with gaining credit for a course. To answer this research question, I will estimate a multilevel logistic regression model with enrollment in credit recovery, not addressing course failure, or enrolling in credit recovery and repeating the course for credit as separate variables on the right-hand side of the equation at the course level. The comparison will be with student-courses that were only repeated for credit. The outcome will be gaining credit for the previously failed course. The same variables from the multilevel logistic regression will be

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[2] The correlates with assignment to credit recovery, repeating a course, or being assigned to neither option are not explored in this study because the multilevel, multinomial logistic regression models, where the four different assignment options are all included as separate levels of the outcome, would not converge.

[3] This model could also be run as a multiple membership model, as students can attend more than one school during this time period. However, only two percent of the sample attends more than one high school, a small enough proportion where a multiple membership model is not necessary.

[4] The ICCs from the baseline model are 0.25 at the school-level, and 0.53 at the student-within-school level, indicating that using a multilevel model is worthwhile.

included in this model, but the coefficients of interest are on the variables for credit recovery, neither credit recovery nor repeating the course, or both options.

The fifth research question asks whether there is a possible crowding out effect of credit recovery, where higher levels of credit recovery over time lead to fewer students accessing other options to address course failure. This question will be answered by examining school-level aggregated enrollments in credit recovery and repeating a course for credit. The model will take the following form:

$$Repeat_{it} = \beta_0 + \beta_1 CR_{i,t-1} + \boldsymbol{X}_{it}\boldsymbol{\beta_k} + u_{it}$$

The variable $Repeat_{it}$ represents the percentage of students who failed a course and later repeated the course for credit at school *i* at time *t*. The variable $CR_{i,t-1}$ represents the percentage of students who failed a course but repeated it through credit recovery at school *i* at time *t-1* (i.e., the lagged credit recovery enrollment). The vector of school characteristics is represented by $\boldsymbol{X}_{it}$, and this includes the same school characteristic as the previous analyses of this paper. The coefficient of interest is β_1. A negative, significant coefficient would indicate that the prior year credit recovery enrollment led to fewer students repeating a course for credit—a possible crowding out effect. Standard errors are clustered at the school level. All of the results are generated using Stata.

Results

Between the 2012-13 and 2016-17 school years, high school students in North Carolina failed 742,462 core courses. Of that total number, approximately 48 percent of the student-course records indicate that the course was neither repeated nor taken through credit recovery, as indicated on Table 2. About 16 percent of courses were later addressed through credit recovery, and almost exactly double that percentage of courses (31.5 percent) were repeated for credit. About five percent of courses were later repeated for credit and taken through credit recovery. Overall, plurality student-course records are not associated with any form of course credit remediation, and repeating a course for credit is the second most popular option.

The most obvious reason why almost half of failed student-course records are not taken through credit recovery or repeated for credit is that these represent students who are not on track to graduate and/or they dropped out of high school. Although 48 percent of student-course records are in this “neither” course makeup category, these records only represent 27 percent of students who fail courses. Students in this category are failing multiple courses, and are either at risk of dropping out before remediating course credit, or have a low graduation probability. Another potential explanation for why almost half of student-course failures are not addressed through credit recovery or repeating a course for credit lies in the requirements for graduating from high school in North Carolina. For some courses (for example, all English courses), students have a specific class they must pass to graduate with no substantive alternatives. For all Math courses as well as select science and social studies courses, students can take different classes to meet the graduation requirements. Approximately 40 percent of the student-course failures that are not addressed are Math courses. These students could elect to take a different Math class that also counts toward high school graduation instead of repeating the course or taking credit recovery (although this might require the student to change their track from college-bound to career-ready).

The next set of analyses address the second research question on how changes over time and across schools affect how students address course failure. To assess within-school changes in credit recovery enrollment, Figure 1 shows the changes over time, within-school, in the percentage of student-course records associated with a failure that was later redeemed through credit recovery. This measure ranges from -100 to 100 percentage point changes, with almost a quarter of schools not changing their percent credit recovery enrollment over time (i.e., the change in percent is zero). Approximately 64 percent of schools increased the percentage of student-course failures that result in credit recovery over time. Three percent of schools increased credit recovery enrollments by more than 50 percentage points.

In order to assess the differences across schools in how students address course failure, I created a measure of credit recovery enrollment that represents the ratio of the number of student-course records that are associated with credit recovery over the number of student-course records that are associated with repeating a course for credit (calculated at the school-level). Figure 2 is a bar graph of the resulting ratios that have been sorted based on the size of the ratio. Each bar represents the ratio for a different school. The ratios range from zero, indicating no students at that school enrolled in credit recovery, to eight, indicating there are eight credit recovery student-course records for every one repeating-a-course student-course record at that school. A dashed line is drawn at the y-value of one because a ratio of one indicates that the school has the same number of student-course enrollments in credit recovery and in repeating a course for credit. As shown on Figure 2, the majority of schools have higher enrollments in repeating a course for credit, since most schools have ratios less than one, although 17 percent of schools (115 schools out of 680) do have more credit recovery enrollments than enrollments for courses repeated for credit.

The ratio of credit recovery to repeating courses for credit did change over time, as shown in Figure 3. Figure 3 is equivalent to Figure 2, except that Figure 3 shows these data by year, beginning with the 2013-14 school year and ending with the 2016-17 school year. The bar charts look very similar for 2013-14 (titled “2014”) through 2015-16, since roughly the same proportion of schools have higher enrollments in repeating a course than for credit recovery. When comparing the 2016 and 2017 graphs, there is a discernable shift in the location, where the ratio of credit recovery to repeating a course records crosses the y-line at one. A higher proportion of schools in 2017 were enrolling more students in credit recovery than in repeating a course for credit. Consistently, from 2012-13 through 2015-16, 15-18 percent of schools had more failed courses remediated through credit recovery than repeating a course for credit. In 2016-17, a third of schools had more credit recovery courses than courses repeating for credit. The mean ratio of credit recovery to repeating a course for credit also jumped above one (to 1.1), in 2016-17, from a mean of 0.79 in 2015-16. Indeed, credit recovery became an increasingly popular option across many schools over time.

While these graphs show overall credit recovery enrollment by school and by school over time, investigating patterns more generally over time is part of answering the second research question. Figure 4 shows trend lines for the number of student-course enrollments that are associated with credit recovery, repeating a course for credit, or neither option (for failed courses only) over time. Enrollments in credit recovery increased between 2012-13 and 2015-16, followed by a slight decline in 2016-17. Credit recovery enrollments are always lower than repeating a course for credit enrollments, although the distance between the two bars does lessen over time. By 2016-17, the difference between the number of repeated courses and the number of credit recovery courses is approximately 10,000, while, in 2013-14, the difference is approximately 40,000. As the number of enrollments in credit recovery and repeating a course for credit increase between 2013 and 2015, the number of courses that are not addressed by either option is decreasing, showing an overall trend towards more course failure being addressed by one of the remediation options.

In order to show these data in a different way, Figure 5 shows these same enrollment numbers as the ratio of credit recovery enrollments over repeat enrollments, or not enrolling in either option by year. In 2013, there was approximately one credit recovery enrollment for every two repeat enrollments (ratio of 0.5). By 2017, there was approximately one credit recovery enrollment for every 1.25 repeat enrollments (ratio of 0.8). In 2013, enrollments in neither option vastly outpaced credit recovery enrollments with only one credit recovery enrollment for every ten course failures that were not addressed (ratio of 0.1). The ratio increases over time as more students are taking credit recovery and fewer students are not addressing course failure, and in 2017, for every credit recovery enrollment, there were just over three course failures not addressed (ratio of 0.37).

The next set of results answers the third research question: whether student and school characteristics predict the likelihood of enrolling in credit recovery instead of repeating the course for credit. The results from the multilevel logit model predicting credit recovery enrollment are listed in Table 3. The outcome is a student-course failure that results in taking a credit recovery course with the comparison being student-course failure that results in repeating a course for credit. Student-course failures that do not result in repeating a course or credit recovery are excluded as well as student-course failures that result in students both repeating a course and taking credit recovery. Table 3 includes three specifications. In the first column, only course- and student-level covariates are included; in the second column, only course and school-level covariates are included; finally, the third column includes all covariates.[5] Across all

[5] Column (3) of Table 3 does not include the percent gifted covariate because the model would not converge with all listed covariates.

specifications, the type of course significantly predicts enrollment in credit recovery. Students have higher odds of enrolling in credit recovery if they are in a social studies course, and lower odds of enrolling in credit recovery if they are in a math or science class.

Results for the student characteristics are relatively consistent across model specifications. Higher eighth grade test score averages of students are associated with lower odds of enrolling in credit recovery. Higher percentages of days that a student is absent (measured for the years they are enrolled in the course) are associated with higher odds of enrolling in credit recovery. Black students are more likely to enroll in credit recovery, while students of other races (i.e., non-black, Hispanic, or white) are less likely to enroll in credit recovery. Students who are gifted, SPED, economically disadvantaged, LEP (model (3) only), and over-aged for their grade area all have lower odds of enrolling in credit recovery.

Models including school-level covariates are listed in columns (2) and (3) of Table 3. Higher percentages of teachers with National Board Certification are associated with lower odds of enrolling in credit recovery. Larger school per-pupil expenditures are associated with increased odds of credit recovery enrollment. Based on the lagged EOC proficiency rate, schools could be responding to lower test score proficiency by lowering the odds that students are assigned to credit recovery. The opposite is the case with the lagged high school graduation rate, which indicates that schools would respond to higher graduation rates by raising the probability of assignment to credit recovery. The odds ratio on the lagged course failure rate indicates that schools could be responding to higher initial course failure rates by decreasing the probability a student is assigned to credit recovery in the following year. Increases in the percentage of black students in the school is associated with a lower odds of credit recovery enrollment, while increases in the percentage of Hispanic students are associated with a higher odds of enrollment in credit recovery. I do not find an association between urbanicity or school type and credit recovery enrollment.

To address whether repeating a course for credit or credit recovery is more likely to result in earning credit for a failed course, Table 4 includes the results from a multilevel logit model predicting whether course credit was earned after failing a course. The reference group is courses that a student repeats for credit only. The odds of earning credit through a credit recovery course are almost 2.5 times higher than the odds of earning credit for a student who repeats the course for credit. Students who do not take credit recovery or repeat a course for credit have an extremely low odds of earning course credit, essentially zero (as would be expected). Students who repeat a course for credit and take the course through credit recovery have a slightly lower odds of earning course credit compared to students who only repeat a course for credit, likely because this sample is student-course records, where the student continues to fail the same course multiple times.

The final research question asks if credit recovery is being used as a supplement to or a substitute for students repeating courses for credit. The results of this analysis are listed in Table 5. The coefficient on the percent of failed courses that are retaken through credit recovery in the previous school year ("Percent Credit Recovery, Lagged") is negative and statistically significant. This coefficient indicates that, for every percentage point increase in credit recovery enrollment in the previous school year, the percentage of failed courses that are repeated for credit in the current school year is predicted to decrease by 0.37 percentage points. Schools, on average, increased the percentage of students in credit recovery from around six percent in 2012-13 to 18 percent in 2016-17. This increase of 12 percentage points in credit recovery enrollment is equivalent to an effect of a 4.44 percentage-point decrease in the percentage of students who repeat courses for credit.

Conclusion

This paper confirms speculations on the part of the media that credit recovery courses are becoming an increasingly popular tool that schools are using to increase the likelihood that students earn credit for previously failed courses. Credit recovery enrollment is increasing in North Carolina, and it is being used to replace or crowd out the option of repeating a course for credit as the preferred strategy to regaining credit for a failed course. Schools could be responding to the success of credit recovery with this particular outcome by increasing credit recovery enrollment. Students are much more likely to regain course credit if they are in credit recovery than if they were repeating a course for credit.

This result could be endogenous, especially if students who are more likely to regain course credit are placed in credit recovery. For instance, in interviews with district officials in North Carolina, officials confirmed that they are more likely to enroll a student in credit recovery if they only barely failed a class, or only failed a class due to absences (i.e., they met all academic requirements but were not allowed to pass due to excessive absences).

Compared to students repeating a course for credit, credit recovery students are lower performing and have higher absence rates, but are not as likely to be SPED or economically disadvantaged. It appears that credit recovery students might be lower-performing in many ways, but credit recovery is less likely to be used for students with disabilities or economically disadvantaged students, indicators that are commonly associated with low academic performance. Schools that are enrolling students in credit recovery are more likely to be advantaged and high-performing in several ways, including higher per-pupil expenditures, higher high school graduation rates, and lower course failure rates.

As credit recovery grows in popularity, it will be important to critically examine who is given access to credit recovery courses and why these decisions are being made. Schools appear to be responding to the increased likelihood of credit-earning of credit recovery students by increasing their credit recovery enrollments, but this decision could have unintended consequences if credit recovery courses are low-quality or detract from the learning environment or rigor of the school. Schools might discover that the productivity of credit recovery could lead to the perverse incentive of high course failure rates if students and teachers are aware that students can easily make up courses through credit recovery. While credit recovery appears to be successful in obtaining course credit for failed courses, future research is warranted to address these other areas of concern.

APPENDIX

Table 1: Estimates of Credit Recovery (CR) Course Enrollment or CR Course Availability

		Sample				
Study	Year	State	District	School	Students	CR Enrollment
Clements, Pazzaglia, & Zweig, 2015	2012-13 SY	New York State	-	99 Schools in New York's Capital Region	-	46% Schools Offer CR (27 schools)
Clements et al., 2015	2012-13 SY	Iowa and Wisconsin	-	168 Schools in Each State (A Statewide Random Sample)	-	71% of Schools in IA; 66% of Schools in WI Offer CR*
Hughes, Zhou, & Petscher, 2015	2007-08 through 2010-11 SYs	Florida	All Districts	All Schools	About 866,000 Students Per Year (All High Schools Students)	4,063 Enrollments in CR in 2010-11; 3,236 Enrollments in CR in 2009-10; 2,053 Enrollments in CR in 2008-09; 259 Enrollments in CR in 2007-08
Queen & Lewis, 2011	2009-10 SY	All 50 States	2,290 Districts (Nationally-Representative Random Sample)	-	-	1,126,000 Enrollments*
Picciano et al., 2012	2008-09 SY	-	-	441 High School Principals		73% of Schools Offer CR (322 Schools)

Note: *Weighted estimate(s). SY is an acronym for School Year. IA is Iowa; WI is Wisconsin

Table 2: Percentage of Students Who Failed Courses by Course Credit Remediation Option

	No Credit Recovery	Credit Recovery	Total
Did Not Repeat	47.58	16.35	63.93
Repeated	31.51	4.56	36.07
Total	79.09	20.91	*N*=742,462

Table 3: Results from a Multilevel Logit Model Predicting Taking a Credit Recovery Course as Compared to Repeating a Course for Credit

	(1) Student & Course Covariates	(2) School & Course Covariates	(3) All Covariates
Fixed Effects			
Math Class	0.59***	0.60***	0.60***
	(0.02)	(0.02)	(0.02)
Science Class	0.80***	0.81***	0.81***
	(0.02)	(0.03)	(0.03)
Social Studies Class	1.18***	1.18***	1.18***
	(0.05)	(0.05)	(0.05)
Average 8th Grade Test Score	0.96**		0.96**
	(0.01)		(0.01)
Percentage of Absences	1.01***		1.01***
	(0.00)		(0.00)
Black	1.15***		1.14***
	(0.02)		(0.02)
Hispanic	0.95		0.94
	(0.03)		(0.03)
Other Race	0.93*		0.92**
	(0.03)		(0.03)
Female	1.00		1.00
	(0.02)		(0.02)
Gifted	0.79***		0.80***
	(0.03)		(0.03)
SPED	0.95*		0.92***
	(0.02)		(0.02)
Economically Disadvantaged	0.91***		0.85***
	(0.02)		(0.02)
LEP	0.93		0.87**

	(0.05)		(0.04)
Former LEP	1.03		1.00
	(0.04)		(0.03)
Overage for Grade	0.81***		0.84***
	(0.02)		(0.02)
Suburb		0.84	0.90
		(0.33)	(0.32)
Town		0.79	0.79
		(0.32)	(0.31)
Rural		0.88	0.9999
		(0.28)	(0.29)
Percentage of Teachers with 3 or Fewer Years of Experience		0.995	0.995
		(0.01)	(0.01)
Percentage of Teachers with National Board Certification		0.94***	0.94***
		(0.01)	(0.01)
Short Term Suspension Rate		0.99	0.99
		(0.01)	(0.01)
Number of Violent Acts per 100 Students		0.99996	1.00
		(0.0002)	(0.0002)
School Per Pupil Expenditures (in 100s)		1.01***	1.01***
		(0.002)	(0.002)
EOC Proficiency Rate, Lagged		0.99***	0.99***
		(0.003)	(0.003)
Percent LEP		0.93	0.94
		(0.03)	(0.03)
Percent Gifted		0.97	
		(0.02)	
Percent SPED		0.99	0.97**
		(0.01)	(0.01)
Percent Chronic Absenteeism, Lagged		0.999	0.999
		(0.01)	(0.01)

Enrollment (in 100s)		1.02	1.02
		(0.04)	(0.04)
HS Graduation Rate, Lagged		1.02**	1.02**
		(0.01)	(0.01)
Course Failure Rate, Lagged		0.96***	0.96***
		(0.01)	(0.01)
Percent Economically Disadvantaged		0.99	0.99
		(0.005)	(0.005)
Percent Black		0.98**	0.98**
		(0.01)	(0.01)
Percent Hispanic		1.10***	1.09***
		(0.02)	(0.02)
Magnet School		1.41	1.42
		(0.36)	(0.37)
Alternative School		0.62	0.82
		(0.53)	(0.68)
Constant	0.39	0.45	0.43
	(0.03)	(0.55)	(0.51)
N	285477	285477	285477
Random Effects			
Between-School Variance (intercept)	1.57	2.52	2.32
	(0.12)	(0.45)	(0.39)
Between-Student Variance (intercept)	1.76	1.79	1.78
	(0.06)	(0.06)	(0.06)
Residual ICC			
School level	0.24	0.33	0.31
	(0.01)	(0.04)	(0.04)
Student-Within-School level	0.50	0.57	0.55
	(0.01)	(0.03)	(0.02)

Exponentiated coefficients; standard errors of logged odds in parentheses. Percentage gifted excluded from model (3) because the model would not converge when including all covariates.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Multilevel Logistic Regression Model Predicting Earning Credit for a Course

	(1) Earned Credit
Credit Recovery Only	2.46***
	(0.18)
No Credit Recovery Did Not Repeat	0.004***
	(0.0003)
Credit Recovery and Repeat	0.82***
	(0.03)
Observations	534835

Exponentiated coefficients; standard errors of logged odds in parentheses; covariates not included for brevity
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Ordinary Least Squares Model Predicting the Percentage of Students Repeating a Failed Course

	(1) Percentage Repeated
Percent Credit Recovery, Lagged	-0.36***
	(0.03)
Observations	1957

Standard errors in parentheses; covariates excluded for brevity; standard errors clustered at the school level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: Change in Percentage of Students in Credit Recovery Within School Over Time

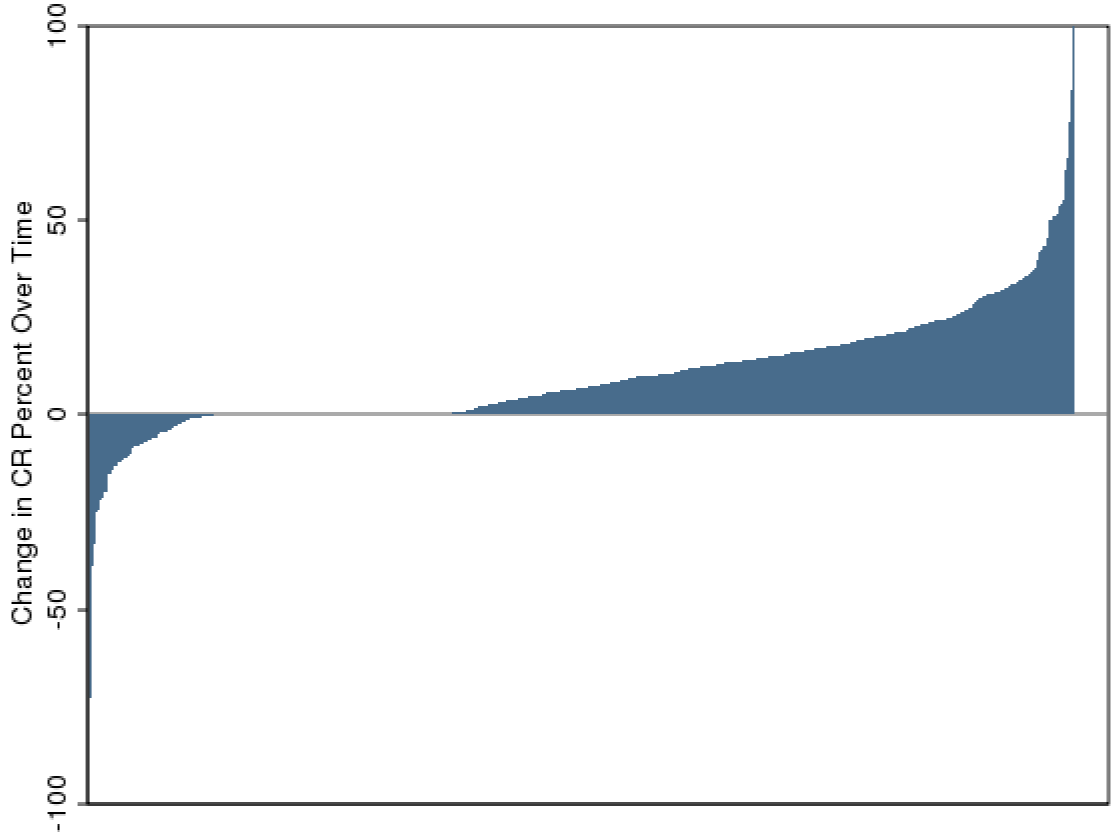


Figure 2: Ratio of Credit Recovery Courses to Repeating Courses for Credit

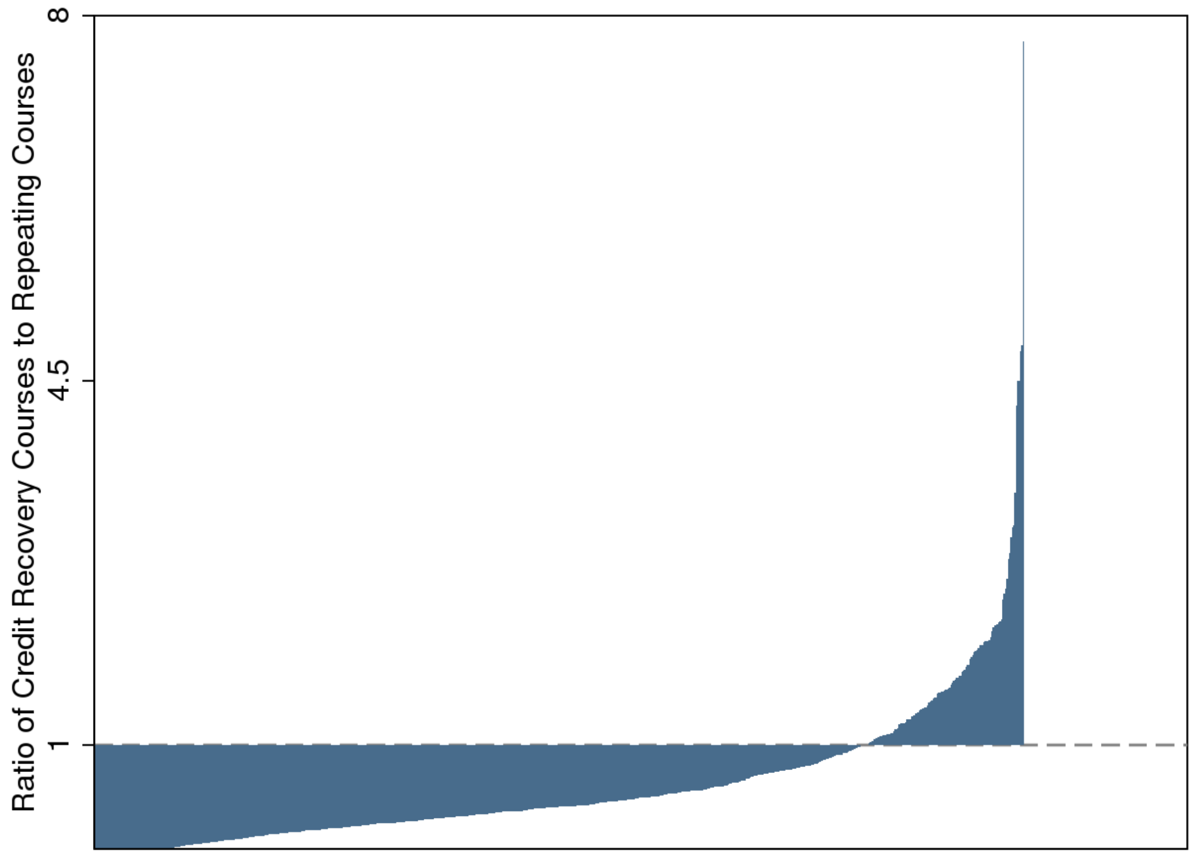


Figure 3: Ratio of Credit Recovery to Repeating Courses Over Time

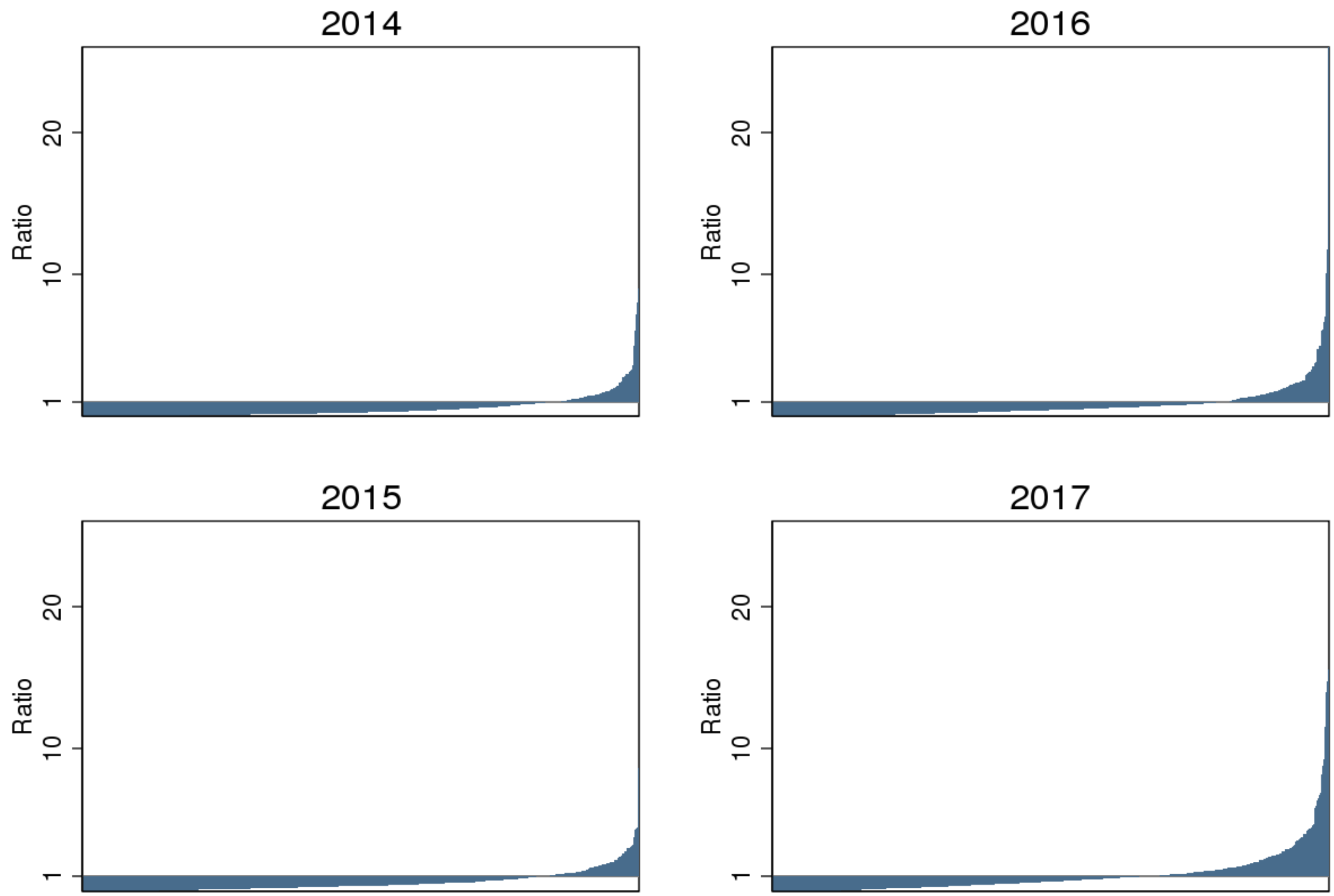


Figure 4: Number of Credit Recovery and Repeating Course Enrollments Over Time

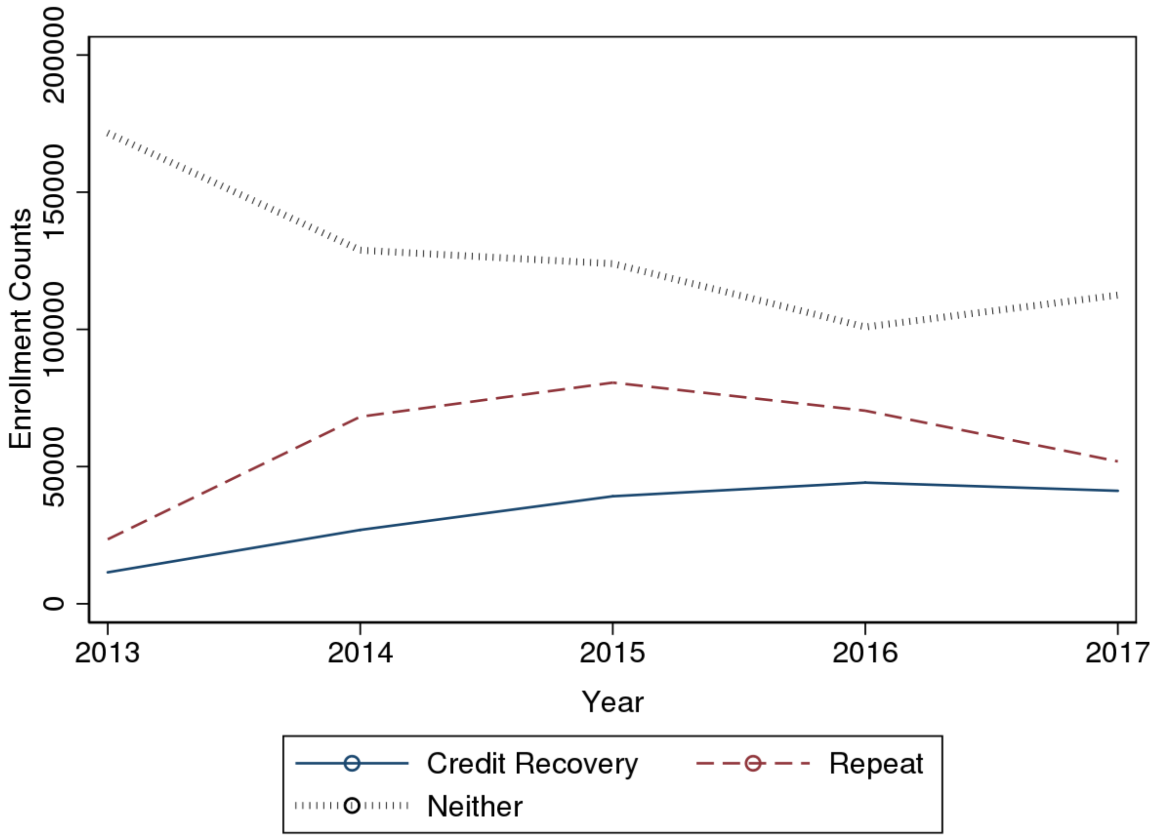
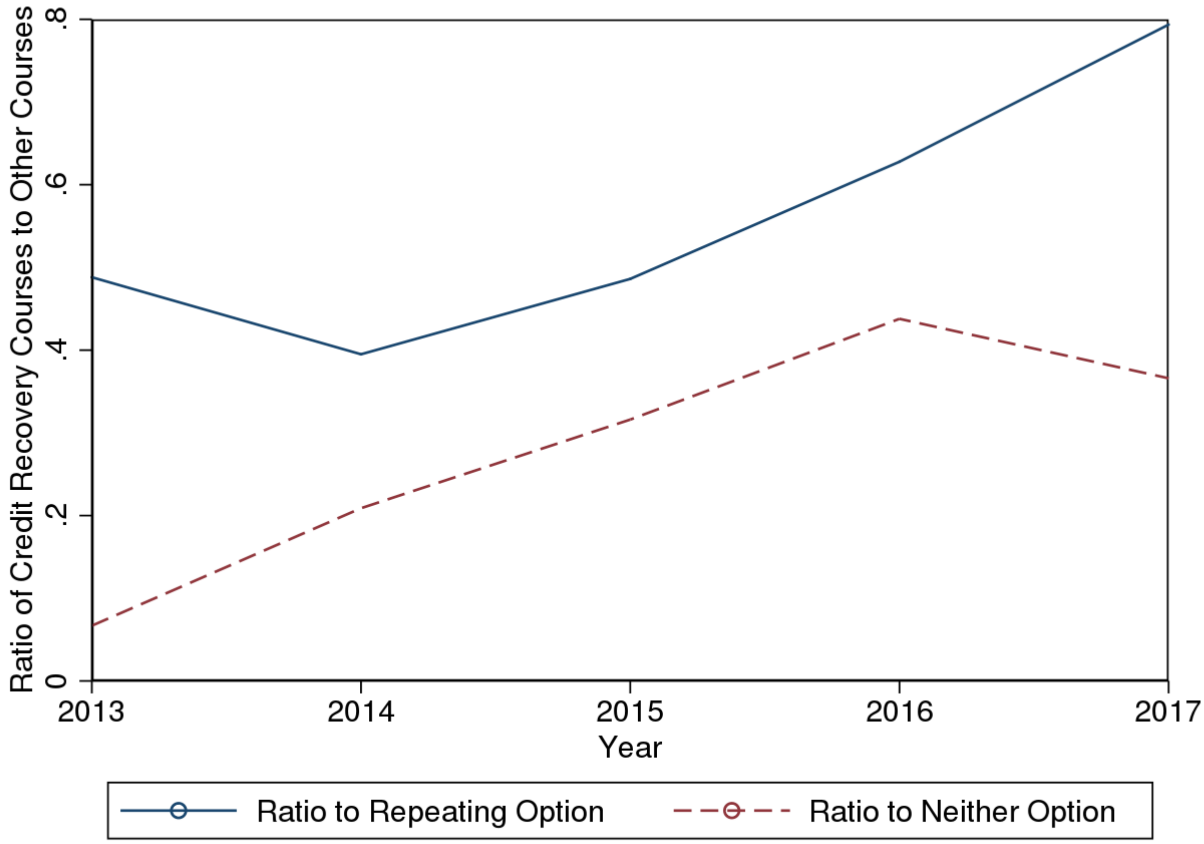


Figure 5: Ratio of Credit Recovery Courses to Repeating Courses Over Time



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CHAPTER II

ARE CREDIT RECOVERY COURSES AN EFFECTIVE INTERVENTION TO ADDRESS COURSE FAILURE?

Introduction

In 1996, the high school graduation rate dropped to a low of 71 percent after three decades of decline and stagnation (since the peak of 79 percent in 1970). Over the last fifteen years, however, the high school graduation rate has bounced back, rising each year since 2002, and reaching a record high of 80 percent in the 2010-11 school year ("Common Core of Data (CCD)," n.d.; "National Center for Education Statistics," n.d.; "U.S. High School Graduation Rate Hits New Record High | U.S. Department of Education," n.d.). As shown in Figure 6, black and Hispanic students historically have lower graduation rates than white students. While the graduation rate of all three subgroups of students has increased, larger gains in graduation rates of black and Hispanic students have closed the gap between the graduation rate of white students and black and Hispanic students by approximately 20 percent—or three percentage points—between 2003 and 2014.

This pattern is also reflected in the status dropout rate—the percent of 16- to 24-year-olds who are not enrolled in school and do not have a high school credential—by income level (see Figure 7). For all groups, the status dropout rate decreased between 2003 and 2014, with the largest decrease for students in the lowest income quartile, for whom status dropout rates decreased approximately 40 percent. The gap in status dropout rates between the lowest and highest income quartiles has closed, dropping 16 percentage points in 2003 to nine percentage points in 2014. While the evidence clearly shows that the graduation rate is increasing overall and by student subgroup, it is unclear why it is increasing.

While students do not graduate from high school for many reasons, state graduation requirements are the only official barrier to graduation. In all but one state (North Dakota), state law sets minimum graduation requirements for all public school students that include earning a certain number of course credits in order to graduate ("Standard High School Graduation Requirements (50-state)," 2016). Prior research confirms that two aspects of course credit requirements lead to lower rates of graduating from high school: increasing state-level credit accumulation requirements and students failing courses (see Allensworth & Easton, 2005; Bowers, 2010; Mac Iver & Messel, 2013; Plunk, Tate, Bierut, & Grucza, 2014). With the graduation rate rising, increased credit accumulation represents a direct plausible explanation for the higher percentage of students graduating from high school and the lower percentage of high school dropouts.

Credit recovery is a tool for students to increase credit accumulation, and has greatly increased in popularity over the last decade. Credit recovery refers to an opportunity for a student who has previously failed a course to retake it through an online course—sometimes with in-person classroom supports—to earn the lost credit (McCabe & St. Andrie, 2012; U.S. Department of Education, Institute of Education Sciences, What Works Clearinghouse, 2015). The Institute of Education Sciences estimated 1.1 million course enrollments in credit recovery in the 2009-10 school year, based on a nationwide survey of public school districts (Queen & Lewis, 2011). Credit recovery courses are intended to target students' weaknesses and speed the time to credit completion by focusing on the course topics student needs to learn. Students typically take credit recovery courses through a for-profit provider of online courses, a state-wide virtual school, or a district-run virtual school (Murin, Powell, Roberts, & Patrick, 2015). The credit recovery options available to students are determined by either the school or the district that maintains contracts with specific providers and state or district-wide virtual schools (Murin et al., 2015; Oliver, Osborne, Patel, & Kleiman, 2009).

In this chapter, I will explore the effectiveness of credit recovery as a tool that students or schools are using in order to graduate from high school or to aid in the prevention of dropping out of high school. In particular, I will address the research questions: (1) To what extent are students who take credit recovery courses less likely to drop out or more likely to graduate from high school than students who fail classes, but do not enroll in credit recovery? (2) To what degree is enrollment in credit recovery associated with a lower likelihood of dropping out or a higher likelihood of high school graduation for black, Hispanic, or low-income students?

Literature Review

Since the early 20th century, high school graduation has represented an important credential for all American students, due to the large economic returns to a high school diploma (Goldin, 1998). While graduation rates in recent years continue to increase, the high school graduation rate in the U.S. is at least 20 percentage points lower than 100 percent, with traditionally disadvantaged subgroups of students having much lower graduation rates (Heckman & LaFontaine, 2010). Evidence indicates that both the accountability movement and the corresponding push for the high school diploma as a signifier of college or career readiness have contributed to the suppression of the graduation rate. High school exit exams and increasing course requirements have both been shown to be associated with lower graduation rates (Holme, Richards, Jimerson, & Cohen, 2010; Howard, Romero, Scott, & Saddler, 2015; Plunk et al., 2014; Reardon, Arshan, Atteberry, & Kurlaender, 2010).

However, a key shift in the accountability movement quietly took place around the 2010-11 school year, when the No Child Left Behind Act began requiring high schools to report their graduation rates (“No Child Left Behind High School Graduation Rate Non-Regulatory Guidance,” 2008). At the same time, the Race to the Top grant competition required applicant states to create a system that would force heavy restructuring of low-performing schools, where low performing was based on both test scores and graduation rates (“Overview Information; Race to the Top Fund; Notice Inviting Applications for New Awards for Fiscal Year 2010; Notice,” 2010). Ten years after test score proficiency was made a national priority, high school graduation was added to the roster of high-stakes accountability targets. With high schools facing sanctions if they had low graduation rates, the key question was: how would they go about increasing the graduation rate?

The Effect of Credit Accumulation or Course Failure on High School Graduation

Students face many institutional and personal barriers to graduating from high school. In a systematic review of the literature on dropping out of high school, Dupéré and colleagues propose a development timeline of different types of factors that lead to students dropping out of high school that includes many different individual, family, neighborhood, and peer characteristics as well as turning points like teen parenting, peer victimization, and financial needs. Between all of these elements of the lifespan and the actual act of dropping out of high school lies *proximal mediators*, which are the actions students take that lead to dropping out (Dupéré et al., 2014). Specifically, all of the points on the development timeline flow through specific causes of dropping out, such as failing classes and the lack of course credit accumulation.

Studies from across the country have confirmed that, even when controlling for demographics, test scores, and other key characteristics, failing courses or low credit accumulation are associated with lower rates of high school graduation. Several studies have used the measure of earning average grades of D or F, finding that students with these low grades are less likely to graduate from high school (Barro & Kolstad, 1987; Bowers, 2010; Neild, Stoner-Eby, & Furstenberg, 2008). In a study of Philadelphia students in the late 1990s and early 2000s, the coefficient on average grades of D or F in ninth grade remained statistically significant after controlling for grades in middle school, test scores, attendance in middle and high school, and several measures of rebelliousness, risk-taking, and academic engagement in middle school (Neild et al., 2008). In a discrete time hazard model estimating risks of dropping out, receiving average grades of D or F in eleventh grade was the strongest risk factor for dropping out of high school, as compared to receiving similar grades between sixth and tenth grade. More specifically, other studies found that failing courses is associated with a lowered rate of high school graduation (Barrington & Hendricks, 1989; Mac Iver & Messel, 2013; Silver, Saunders, & Zarate, 2008). For the class of 2005 in the Los Angeles Unified School District, failing ten percent or more of high school courses is associated with extremely low odds of graduating high school, after controlling for eighth grade academic performance.

Many schools and districts now use a standard *on-track indicator* to assess whether students are at high risk for dropping out of high school. The use of these on-track indicators is often traced back to the work of the Consortium on Chicago School Research (CCSR), which found that 81 percent of on-track students—defined as those who received no semester Fs and accumulated at least five credits in ninth grade—graduated in four years, while only 22 percent of off-track students graduated in four years, regardless of middle school performance (Allensworth & Easton, 2005). The validity of the on-track indicator has since been confirmed in New York City, two urban Midwestern school districts, and five Texas school districts (Hartman, Wilkins, Gregory, Gould, & D'Souza, 2011; Kemple, Segeritz, & Stephenson, 2013; Norbury et al., 2012). While the on-track indicator has proven useful to school districts as a way to identify students at risk for dropping out of high school, the effective solutions that high schools can implement to prevent students who fail courses from dropping out have not been clearly identified in prior research.

Solutions Available to High Schools to Address Course Failure

The most proximal solutions to address course failure or low credit accumulation are for the students to earn the credits they lost when they failed the course. Schools have historically done this in several ways: remedial courses in the summer or after school, repeating the course in full, or grade retention (i.e., repeating all of the courses for that grade level). While most of the evidence investigating the effects of grade retention comes from elementary grades, the results are unequivocal: grade retention leads to lower student engagement, lower attendance, and increased risk of dropping out of high school (Christle, Jolivette, & Nelson, 2007; Howard et al., 2015; Janosz, LeBlanc, Boulerice, & Tremblay, 1997; Jimerson, 2001; Jimerson, Anderson, & Whipple, 2002). Using two longitudinal samples of students in Montreal, Quebec, Janosz and colleagues (1997) found that grade retention in high school leads to increased odds of dropping out, even when controlling for student grades.

Remedial courses solely for students who previously failed the course, which are usually offered as summer school or after school programs, are popular strategies for earning lost course credit (Cooper, 2001; Cooper, Charlton, Valentine, Muhlenbruck, & Borman, 2000; Lauer et al., 2006; McMillan & Snyder, 2002). However, the research literature has focused on the efficacy of these strategies regarding student test scores, with no available studies linking participation in these programs to high school graduation or earning course credit. While after school or summer school courses could effectively address course failure, such that students who fail courses but participate in these programs later graduate from high school at higher rates, the evidence base on the efficacy of remedial coursework is extremely limited.

Only one available study investigates the effects of repeating a course in full after course failure on earning course credit the second time in the class. In a study of an urban California school district, researchers investigated how often students repeated Algebra I between 2006 and 2012, and whether the students who repeated Algebra I passed the course the second time. They found that 44 percent of students in the district repeated Algebra I, with 89 percent of students who initially earned a D or an F in Algebra I repeating the course. Three quarters of students who repeated Algebra I passed the course the second time (Fong, Jaquet, & Finkelstein, 2014).

Currently, high schools—particularly low-performing high schools—are left with the knowledge that they are held accountable for graduation rates, and students are less likely to graduate from high school if they fail courses. However, the research-based solutions assessing the means to both prevent course failure and address course failure are severely lacking. Yet, high school graduation rates have been increasing over the last fifteen years (see Figure 6). This is the point when credit recovery should enter the conversation as a possible strategy for increasing graduation rates. If students who fail courses can earn the credits they lost through course failure, then they would theoretically be more likely to graduate from high school. However, just as with remedial after school and summer school programs, there is no evidence that credit recovery courses lead to higher credit accumulation and a higher likelihood of high school graduation. Only one study to date has assessed the hypothesis that credit recovery will increase high school graduation rates. In a study of credit recovery courses offered through the state-run North Carolina Virtual Public School, the authors found that, compared to students who retook a course traditionally, either during the school year or over the summer, credit recovery students were less likely to graduate from high school (Stallings et al., 2016). This study did not include credit recovery course-taking from privately-run credit recovery providers; instead, it examined a relatively early time period for credit recovery enrollment (2008-09 through 2011-12), and used only covariate-adjusted regression estimates instead of methods that could yield a plausibly causal estimate of the effects.

In this chapter, I investigate the efficacy of credit recovery as a tool to increase high school graduation rates for all students, and for students who are less likely to graduate from high school, such as students of color and low-income students. The data are from North Carolina Public Schools, although the results are likely generalizable to other states because North Carolina has a similar credit recovery system as many other settings. North Carolina has a publicly-run online course provider called the North Carolina Virtual Public School, and allows districts and schools to have contracts with privately-run providers of credit recovery. At least 40 states have publicly-run providers of credit recovery, and privately-run credit recovery providers are very popular nationwide (Watson, Gemin, & Ryan, 2008). In addition to being a large, diverse state with schools that are similar to schools in many other localities, North Carolina schools have a common configuration of credit recovery offerings as compared to other states.

Methods

Data and Sample

The data for this project include student-level records from an administrative database, including all students enrolled in public schools in North Carolina. This administrative database is maintained by the Education Policy Initiative at the University of North Carolina at Chapel Hill (EPIC), and includes longitudinal information on students, their schools, and their teachers. Student course roster files and student grade records are particularly important data files for this project, as these files identify students who have enrolled in credit recovery.

The sample in this study is restricted to students who failed a core, required academic course anytime in high school (see "High School Graduation Requirements," n.d.).[6] Students who fail courses can be identified between the 2012-13 and 2016-17 school years. This sample restriction is due to credit recovery being an intervention that specifically addresses course failure. The sample that only includes students who failed at least one course will allow students who qualified for treatment (i.e., credit recovery) but did not receive the treatment to be compared with those students who did receive treatment. Within this sample, some students will be identified as taking a credit recovery course (i.e., the treatment group), while other students will repeat the course in full in a traditional fashion during a class period, after school, or in summer school (termed "repeating a course for credit"). A third category of students will appear to neither repeat the course for credit nor take the course through credit recovery.

[6] Regardless of year or track, students are required to complete four years of English, at least three math courses, Biology with at least one other science course, and a minimum of two social studies courses. Go to http://www.ncpublicschools.org/docs/curriculum/home/graduationrequirements.pdf for more information.

The analytical sample is organized as a panel data set with two cohorts of students: first-time ninth graders in the 2012-13 and 2013-14 school years. The panel only includes these two cohorts because they are the only two cohorts that have enough information to include full course-taking information in high school up to an on-time graduation date four years after entering high school.

Measures

Credit Recovery Enrollment. The treatment variable in this study is whether or not a student is enrolled in credit recovery anytime in high school, focusing only on core content courses required for high school graduation ("High School Graduation Requirements," n.d.). Since students can be enrolled in multiple credit recovery courses, models will include either an indicator variable of the student having taken any credit recovery course, or a count variable indicating the number of credit recovery courses the student was enrolled in. I can also explore non-linear effects of credit recovery course-taking based on the number of courses a student enrolls in, specifically examining whether there is a threshold effect where the effects of taking credit recovery are more pronounced after a certain number of credit recovery enrollments.

Outcome Variables. The two dependent variables for this study are dropping out of high school in North Carolina and graduating from high school within four years. Students will be considered high school dropouts if they are no longer enrolled in a North Carolina public high school four to five years (four years for 2013-14 cohort and five years for the 2012-13 cohort) after entering ninth grade, and there is no record of their having graduated from high school. The technical definition of "dropout" for North Carolina Public Schools is a student who was enrolled in a North Carolina Public School the previous year, but does not enroll in any North Carolina Public

School by day 20 of the following school year, excluding students who officially transferred out of North Carolina Public Schools, were expelled, left the country, or have a serious illness. High school graduation is determined through the graduation file, indicating whether a student graduated from high school in a particular year. To be a high school graduate within four years, the student must have graduated from high school within four years of entering ninth grade (i.e., the official definition used by federal accountability systems).

Covariates

All behavioral and academic covariates are measured in the year prior to entering high school, so that all of these covariates are measured prior to the treatment. Measuring academic or behavioral covariates at the same time or after credit recovery course enrollment runs the risk of including mediators between credit recovery and the outcomes in the model. I avoided including mediators in the models that estimate effects of credit recovery, since including mediators could attenuate the treatment effect estimates.

This study includes many student covariates measured in middle school. Student race/ethnicity—in particular, whether or not a student is Hispanic or black, and whether or not the student is in a family that is economically disadvantaged—are covariates, and are part of a student subgroup analyses. Students' prior academic performance is measured through test scores, enrollment in accelerated or remedial courses, grade point average, and whether or not they failed a course in eighth grade. Students are enrolled in accelerated courses if they are enrolled in a course that is designed to be offered to students at a higher grade level when in eighth grade. For instance, students enrolled in Math I as eighth graders are enrolled in an accelerated course, since Math I is typically offered in ninth grade. Whether a student is enrolled in remedial courses is determined in the same fashion as accelerated courses, but for enrollment in courses designed for lower grade students. Student attendance information will be included from middle school, and will be operationalized as the percentage of school days that a student is absent in eighth grade. Other covariates include gender, whether the student is or was designated as Limited English Proficient (as of eighth grade), whether the student is gifted, and whether the student is enrolled in special education services (SPED).

Empirical Framework

The goal of this study is to assess to what extent enrolling in credit recovery courses leads to a higher likelihood of graduating from high school for students who fail core, required courses in high school as compared to students who repeat courses for credit (the other option for regaining course credit). The ideal empirical framework for this study would be to randomly assign students to credit recovery and repeating courses for credit. If students who failed a core, required class are randomly assigned to take credit recovery courses or repeat the course for credit, the difference between the credit recovery students' outcomes and the outcomes of students who repeat courses for credit would be an unbiased estimate of taking a credit recovery course compared to repeating the course. Since this study will be using secondary data, and random assignment to credit recovery cannot be used, the methodology utilized must attempt to approximate random assignment by applying other approaches for inferring causal effects.

The empirical framework will also need to address three levels of endogeneity in order to provide estimates that can arguably be considered causal effects: cohort-level, school-level, and student-level. At the first level, I include two cohorts in this study. These cohorts might have had differential access to credit recovery for reasons that could be correlated with the outcomes. For instance, one cohort of students might have had more credit recovery courses available to them than the other cohort, leading to a different group of students enrolling in credit recovery that differ in ways correlated with the outcomes. At the second-level, credit recovery assignment might vary between schools due to between-school differences correlated with the outcome. For example, schools with lower per-pupil expenditures might be more likely to offer credit recovery, since it is cheaper than having students retake the course for credit. Assignment to credit recovery would be biased to the extent that lower per pupil expenditures is correlated with dropping out or graduating from high school. The third-level of endogeneity concerns within-cohort and within-school student assignment to credit recovery—in other words, why some students who fail core, required classes take credit recovery courses, while other students repeat the course. Students might be assigned to credit recovery for reasons that are correlated with their likelihood of graduating from high school, such as academic ability, student attendance, and participation in higher-level course work. I take two approaches to address these three levels of endogeneity: fixed effects and matching.

In order to address endogenous differences between cohorts and between schools, the models will include cohort-by-school fixed effects, such that only students who failed courses within the same cohort in the same school are compared to each other. Cohort-by-school fixed effects account for between-cohort and school factors, such as the availability of credit recovery courses, the likelihood of assignment-to-credit recovery based on the school in which a student is enrolled, and the availability of credit recovery courses based on the year that could be correlated with credit recovery enrollment and the outcomes of interest.

A preferable strategy to address the third-level of endogeneity would be to estimate models using student fixed effects. A student fixed effects model would eliminate the between-student variation that likely predicts which students are assigned to credit recovery or not. However, the outcomes of interest occur only once, as in students only graduate from high school once and are either high school dropouts or graduates. Since the outcomes do not vary within students over time, a student fixed effects model will not be possible.

The next best strategy available to address within-cohort and school-selection bias is matching. Matching categorizes students within the sample by their likelihood of assignment to credit recovery in order to implicitly compare only students with a similar probability of assignment to credit recovery. Rosenbaum and Rubin (1983) proposed that these probabilities of assignment (i.e., Mahalanobis distance) can produce a sample where assignment to treatment is independent of the outcome in that sample, an assumption known as strong ignorability. According to Stuart (2010), the likelihood of this assumption holding true using a matching strategy is reasonable with a set of covariates that predict both assignment and the outcomes of interest. For this study, the goal is to produce credit recovery and repeating-a-course-for-credit samples that, conditional on covariates measured prior to high school, contain students with similar likelihoods of participating in credit recovery and, in the absence of participating in credit recovery, graduation or dropout. Following the advice of Stuart, the covariates that this study include are likely highly correlated with assignment to credit recovery and the outcomes of interest. The matching procedure (described in detail below) reduces bias in assignment to treatment to the extent that credit recovery assignment is measured by the covariates. Many prior studies using within-study comparisons between randomized experiments and non-randomized samples have shown that using a matching strategy with a robust set of covariates reduces bias in the treatment effect by over 90 percent (see Bifulco, 2012; Shadish, Clark, & Steiner, 2008).

A robust group of covariates is included in the matching procedure. This group contains the basic student information that is common to matching procedures: student race/ethnicity, gender, and an indicator of socioeconomic disadvantage. Also included are key indicators of the students' learning capabilities that are highly predictive of high school graduation probability and are likely taken into account when assigning students to credit recovery courses: whether the student is SPED, whether the student is gifted, and whether the student is Limited English Proficient (LEP). Their test scores from eighth grade are also part of the matching procedure because their academic ability influences the likelihood of high school graduation, and has the potential to influence assignment to credit recovery. Students with higher academic ability might be more likely to enroll in credit recovery because these students might have failed the prior course due to issues like attendance instead of a lack of content knowledge, and students with lower academic ability might be discouraged from taking credit recovery courses because these students need more guidance and scaffolding than an online platform can provide. Enrollment in accelerated and remedial courses in middle school are also included, as they are recognized indicators of high school success. These variables could also be correlated with credit recovery assignment if, for instance, students who enrolled in accelerated courses are more likely to be college-bound and desire to have the failing grade expunged from their transcript, thus leading them to repeat the course for credit. Similarly, students who enrolled in remedial courses might be more likely to take a credit recovery course because their academic struggles led them to have little concern about their high school transcript. It is this same argument that leads to the inclusion of eighth grade GPAs in the matching procedure. The eighth grade GPA will predict both of the outcomes, since this is an indicator of both motivation and academic ability. Students with higher eighth grade GPAs are also more likely to want to maintain a higher high school

GPA, leading them to be more likely to repeat a course for credit. A closely aligned variable is whether the student failed a course in eighth grade. Failing a course in eighth grade also indicates students' motivation and academic ability, which are correlated with the outcomes as well as a student's comfort with having a failing grade listed on their transcript. Student attendance in eighth grade is the final covariate included in the matching procedure. Student attendance in eighth grade is indicative of attendance in high school, thus predicting high school success. Attendance might also be a key way that students are assigned to credit recovery, since students who have poor attendance might be seen as being a better fit for a flexible, online platform than a structured, traditional course.

The matching procedure includes both coarsened exact matching and matching based on Mahalanobis distance. Matching is performed within cohorts and schools. To improve the quality of the matches and the plausibility of approximating a random sample, I implement coarsened exact matching, where students are matched exactly on the quintile of their average eighth grade test scores and their economically disadvantaged status. These two covariates are selected because they are both highly predictive of credit recovery enrollment. If a member of the treatment or comparison group does not exactly match on these covariates with a student within a school and cohort with the opposite status, then that student is dropped. After students are matched exactly on eighth grade test score quintile and economically disadvantaged status within cohorts and schools, the remaining students are matched on the full set of covariates. The matching is done using a Mahalanobis distance measure, where students who had enrolled in credit recovery are matched based on the Mahalanobis distance measure to members of the comparison group. Mahalanobis distance is a multidimensional measure of the similarity between members of the treatment and comparison group based on the available covariates.

Mahalanobis distance is well-suited for this study because it performs well with covariates that are likely to have non-linear relationships with each other (Rubin, 1980). Students who only repeat courses for credit are excluded from the sample if they are not one of the top five matches, according to the Mahalanobis distance, for any member of the treatment group with which they were matched during the coarsened exact matching procedure.

The samples that result from the matching procedure are assessed for covariate balance using two methods based on the advice of Stuart (2010): the standardized difference in means and the ratio of standard deviations between the treated and comparison groups. The standardized difference in means should all be less than 0.25. The ratio of standard deviations should be between 0.5 and 2. As shown in Table 6, the matching process successfully created a matched sample using these parameters. The within-group means and standard deviations are shown for each covariate, with the first line including information on credit recovery (CR) students, and the second line showing the comparison group (Not CR) for each covariate. All standardized differences are below 0.25 (the largest difference is 0.14), and all standard deviation (SD) ratios are between 0.98 and 1.25.

The final models include cohort-by-school fixed effects with all of the covariates mentioned in the data and measures sections above using the matched sample. The models will be estimated using logistic regression, since all outcomes are binary. The model takes the following form:

$$(1)\ \Pr(Y_{csi} = 1|G) = \frac{1}{1 + e^{-G}}$$

$$\text{where } G = \beta_1 CR\_Student_i + \boldsymbol{\rho X_i} + \delta_{cs} + u_{csi}.$$

The outcome, Y_{csi} represents whether student *i* in school *s* and cohort *c* graduated from high school or dropped out of high school, depending on the specification. The coefficient of interest is on the β_1 coefficient, indicating the effect of taking credit recovery on the outcome. The model includes a vector of individual student characteristics, $\boldsymbol{X_i}$, as well as a cohort-by-school fixed effect, δ_{cs}, and an error term, u_{csi}. All models are rerun with interactions between the credit recovery variable and the variable indicating that a student is black, Hispanic, or low-income in order to answer the research question about whether or not the treatment effects are heterogeneous for traditionally lower performing student subgroups. The equation below substitutes the variables black, Hispanic, and low-income for the term “Moderator”:

$$(2)\ \Pr(Y_{csi} = 1|G) = \frac{1}{1 + e^{-G}}$$

where $G = \beta_1 CR_{Student_i} + \beta_2 Moderator_i + \beta_3 Moderator_i \times CR_{Student_i} + \boldsymbol{\rho X_i} + \delta_{cs} + u_{csi}$.

The coefficient of interest is β_3, indicating the differential effect of credit recovery on students based on their race or low-income status.

In order to assess whether the association between credit recovery enrollment and the outcomes are sensitive to the dosage of credit recovery, I estimate the following model:

$$(3)\ \Pr(Y_{csi} = 1|G) = \frac{1}{1 + e^{-G}}$$

where $G = \beta_1 CR_{Student_i} + \beta_2 Number\_CR_i + \beta_3 Number\_CR_i^2 + \beta_3 Moderator_i \times CR_{Student_i} + \boldsymbol{\rho X_i} + \delta_{cs} + u_{csi}$.

Dosage is measured through the $Number\_CR_i$ and $Number\_CR_i^2$ variables, since initial models indicate a quadratic relationship between the number of credit recovery courses and the outcomes. Combining the coefficients β_1, β_2, and β_3 indicate the association between credit recovery dosage and the outcome.

Limitations

While every attempt is made to estimate an unbiased treatment effect of credit recovery on high school graduation, several different sources of endogeneity will likely remain unaddressed. For instance, if students are assigned to credit recovery courses in schools in a highly personalized manner, such that two students who look identical according to their data (e.g., same middle school attendance, test scores, and behavior) are assigned to credit recovery based on specific information about those students that is also predictive of their high school graduation propensity, then the treatment effect estimates will be biased. The extent to which this is true is unknown and likely highly varied both across and within schools. Most likely, students are assigned to credit recovery in some mixture of random and highly purposeful ways, with some schools perhaps using one approach or the other, while others mix the two. However, purposeful assignment only biases the estimates to the extent that this purposeful assignment is not correlated with a covariate such as gender, test scores, or attendance.

Another limitation of this approach is that the attempt to create a sample that approximates random assignment of credit recovery or repeating a course for credit inherently limits the external validity of the findings. Each step of the empirical framework leads to members of the original sample being excluded from analysis due to missing data, not matching with a member of the opposite treatment condition, or through estimation of the logistic regression. As shown in Table 7, the original samples for credit recovery and students who repeat courses is reduced from original sample sizes of 38,282 and 40,300 to 29,402 and 25,138, respectively. The two restrictions that particularly reduced my sample size were the inclusion of the eighth grade covariates and the matching process. To the extent that students who were not enrolled in public school in North Carolina prior to entering ninth grade are different, the generalizability is restricted to only the kind of student who does have available eighth grade information. For students who were excluded because of the matching process of logistic regression estimation, I was able to gain a more complete understanding of how the exclusion of these portions of the original sample could affect generalizability. Table 8 compares the mean of several covariates between the original and final samples (students who were not missing demographic data, but who were missing eighth grade information will also be part of the original sample for demographic data). As shown in Table 8, slight differences in the mean composition of the samples occurred from the original sample to the final. For instance, the final sample has a slightly higher proportion of black students and economically disadvantaged students. These differences do not limit the internal validity of my results, but do speak to limits of the external validity of the findings below.

Results

The results for the main specification are shown in Table 9, with odds ratios shown for each coefficient in the two main models.[7] Overall, enrollment in credit recovery leads to a statistically significant positive effect for each of the outcomes. Compared to students who fail courses and repeat the course(s) for credit, students in credit recovery have higher odds of graduating from high school within four years as well as having lower odds of dropping out of

[7] The odds ratios on the variables indicating whether a student is black or Hispanic are both significant and indicate that being black or Hispanic is associated with higher odds of graduating from high school and lower odds of dropping out of high school. While this result is unusual given the literature on the chronic under-attainment of students of color, within the sample of students who fail courses, the data indicate that these students have higher graduation rates and lower dropout rates. Descriptively, the graduation rate for white students who fail courses is 63 percent, while 65 percent of Hispanic students and 67 percent of black students who failed classes graduate from high school. For dropping out, 32 percent of white students who fail classes drop out, while 24 percent of black students and 26 percent of Hispanic students who fail classes drop out.

high school. The odds of dropping out of high school are 0.4 times lower for credit recovery students as compared to the odds of dropping out of high school for students who repeat a course for credit. For graduating from high school within four years, taking credit recovery is associated with 1.2 times higher odds of graduating than students who repeat courses in full.

The results of the moderation analysis are shown in Table 10 for the covariates of interest only. Columns 1 and 4 show the results for interactions for black students, columns 2 and 5 show the results for the interactions for Hispanic students, and columns 3 and 6 show the results for the interactions for economically disadvantaged students. For black and Hispanic students, taking credit recovery is associated with a lower likelihood of dropping out of high school compared to non-black/Hispanic credit recovery students. However, black and Hispanic credit recovery students do not have higher odds of graduating from high school compared to non-black/Hispanic credit recovery students. Being a black or Hispanic credit recovery student is associated with a decrease in odds of dropping out by approximately 0.1 from the baseline effect sizes of credit recovery. Economically disadvantaged credit recovery students are less likely to drop out compared to non-economically disadvantaged credit recovery students, with a decrease in odds of dropping out of about 0.2 from the baseline effect size. In the model in column (6), the coefficient on credit recovery loses statistical significance and is attenuated, and the coefficient on economically disadvantaged credit recovery students is significant. This result indicates that economically disadvantaged credit recovery students are more likely to graduate from high school, while non-economically disadvantaged credit recovery students are no more likely to graduate from high school than students who repeat courses for credit.

I also explore the associations between the outcomes and the number of credit recovery courses a student takes in order to assess whether the effects of credit recovery vary by the dosage of credit recovery. As shown in Table 11, the coefficient on the number of credit recovery courses is significant and less than one for the graduation outcome, indicating a diminishing return to taking more credit recovery courses. After taking six credit recovery courses, credit recovery students are no more likely to graduate from high school than students who repeat courses for credit. However, I do not find a diminishing return to credit recovery for the outcome of dropping out of high school. For each additional credit recovery course, students have an additional 0.15 lower odds, in addition to the base effect size of 0.20 lower odds. For reference on the number of credit recovery courses in which students enroll, see Figure 8. While most credit recovery students take one course, the maximum number is 16 and the average is two. For the average credit recovery student taking two credit recovery courses, their odds of dropping out is half that of the odds of dropping out for students who only repeat courses for credit.

Robustness Checks

Several robustness checks are performed to see whether the results are sensitive to the specification of the model as well as to potential threats to the validity of the results. Because matching was performed with replacement, the traditional estimation using a matched sample would weight to account for members of the comparison group who were used as matches for multiple members of the treatment group. The fixed effect logistic regression strategy is unable to include probability weighting, so as a robustness check, I re-ran all of the models using a fixed effects linear regression both with and without probability weights. Overall, these results were qualitatively very similar to the logistic regression results. The weighted and unweighted versions of the results were almost identical to each other, giving strength to the claim that the validity of the fixed effect logistic regression results is not compromised by the inability to include probability weights that are based on the number of times a student who only repeated courses is matched to a credit recovery student.

While eighth grade test scores are predictive of assignment to credit recovery, attendance is also an important indicator of credit recovery enrollment because of its importance in how students can be assigned to credit recovery. In interviews with the author, at least one school district indicated that they place chronically absent students in credit recovery because the flexible platform better meets their needs. The sample was re-matched with coarsened exact matching on the eighth grade absence rate quintile instead of the eighth grade test score quintile. The balance checks indicated good balance with this new matched sample using the same balance metrics as the main results. Running the models with this new matched sample yielded almost identical results as those using the prior matched sample. This test indicated that coarsened exact matching on both test score and attendance yields the same results, giving more plausibility to the idea that these matched comparison groups approximated a random sample.

One threat to causality is the potential endogeneity stemming from students who fail multiple courses when assignment to credit recovery is related to the number of courses they fail as well as the outcomes. In order to address this source of endogeneity, I restricted the sample to only students who have failed one class. After matching within the sample of students who only failed one class, the matched sample has extremely good balance (largest standardized difference is 0.06, standard deviation ratios are bounded by .96 and 1.02). The results from the main specification are very similar in the size and direction of the odds ratio, although the odds ratio on credit recovery when the outcome is graduated from high school within four years loses statistical significance, likely due to the smaller sample size. Overall, the results are similar enough such that this robustness check indicates that the main specification results are not biased by differential assignment of students who fail multiple courses.

For students who fail a course associated with an end-of-course exam (EOC), additional information is available that can be utilized to find a comparable comparison group to credit recovery students. The main analysis does not include information on EOCs because students might not have failed an EOC course (i.e., Math I, English II, or Biology), and consequent EOC scores are potential mediators indicating learning associated with follow-up courses in those subjects. Students who take an EOC credit recovery course are required to retake the EOC after they complete the course online. Students who repeat a course for credit only have to repeat the EOC if the student's initial score was below a Level 3 proficiency. However, if I include information only on the first score a student received on an EOC, then this score would have occurred prior to the student's enrolling in credit recovery or repeating a course for credit. While there are endogeneity concerns with this score, as a robustness check, the initial EOC scores are useful.

In order to properly include EOC scores, the sample is restricted to only students who failed one or more EOC courses. I ran four robustness checks. The first three only included students who failed either Math I, English II, or Biology, where credit recovery assignment is only determined by credit recovery enrollment in that particular EOC course. The credit recovery students are matched to the comparison group using the test score quintile for the initial EOC score instead of their eighth grade score (although the eighth grade score is still included in the matching process and is a covariate in the models). The fourth check includes all students who failed at least one of the three EOC courses. The test score utilized for matching is an average of the standardized scores for the EOC course or courses they failed. All four robustness checks using EOC scores ended up with matched samples that show good balance using the same metrics as those with the main specifications. Regardless of the model, all models using the EOC information and samples have results that are very similar to the main specification in statistical significance, direction of findings, and with similar odds ratios. The results are robust to specifications, restricting the sample to only students who failed the same EOC course matching them to each other based on their initial EOC exam score.

Conclusion

While many have hypothesized that credit recovery courses have contributed to the rising high school graduation rate, this study shows empirically that credit recovery is associated with higher odds of graduating from high school and lower odds of dropping out. Using highly sophisticated methods that account for many likely areas of bias, this study found that credit recovery leads to a higher likelihood of graduating from high school and a lower likelihood of dropping out of high school compared to students who fail courses and repeat them for credit. Students who fail courses in most high schools are faced with two options to make up for that failed credit: repeat the course in full (over the summer, after school, or during the school year) or take the course through credit recovery. This study shows that the preferred alternative to raising the high school graduation rate is credit recovery.

One of the remaining concerns, however, is what happens to credit recovery students after high school. High school graduation is not an end in itself. The expectation is that high school graduates are "college or career ready." Whether credit recovery students are as college and career ready as their peers who repeat courses for credit is not assessed in this study. The extent to which credit recovery students are prepared for college-level coursework or have gained the necessary knowledge for their future career is an important area of future study. While this study addresses whether credit recovery could be leading to higher graduation rates, this study does not address other questions that arise in discussions of credit recovery. For instance, many have wondered if credit recovery courses are rigorous enough to be an appropriate intervention for course failure, or if credit recovery students are learning the same material they would have learned with a face-to-face instructor.

While the empirical design of this study seeks to approximate random assignment, I am unable to rule out the possibility that these results are simply due to students with a higher likelihood of graduating from high school enrolling in credit recovery. In conversations with school districts, several districts indicated that they assign students to credit recovery based on very specific criteria, which could be indicative of their likelihood of graduating from high school. These policies are designed to assign students who either met the academic benchmarks to pass the class but failed due to policies about student attendance (i.e., they were absent too many days to pass), or students who just barely failed to meet academic benchmarks (i.e., their numerical grade was very close to passing). Districts with these policies do allow students to appeal to the district to allow them to take credit recovery even if they do not meet the criteria, but the district then has discretion about allowing students to take credit recovery. To the extent that these policies are systematically used across the state, the results could solely be indicating selection bias instead of the effectiveness of credit recovery.

The relative merits of credit recovery are not explored in this study, but are important areas of concern to be addressed by future work. Many have suggested that credit recovery courses are low-quality, representing a way that schools are gaming the system in order to graduate more students without actually meeting the spirit of graduation requirements. This study validates the utility of credit recovery in increasing the likelihood of graduation at the student level, but the possibility remains that these courses could have deleterious effects in other ways. For instance, students could be learning less in school and spending less time on-task if they enroll in credit recovery. Additionally, students often take multiple credit recovery courses, indicating a potential perverse incentive to fail more courses the first time in order to spend additional time in credit recovery. The extent to which credit recovery students are prepared for higher education or are ready to start a career is also important to assess. Future research should address these types of questions.

APPENDIX

Table 6: Balance Check After Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.43	0.49	0.08	0.99
	Not CR	0.47	0.50		
Student is Hispanic	CR	0.17	0.38	0.14	1.16
	Not CR	0.12	0.33		
Student is Other Race	CR	0.08	0.27	0.06	1.11
	Not CR	0.06	0.24		
Student is Female	CR	0.37	0.48	0.08	0.98
	Not CR	0.42	0.49		
Student is Gifted (8th Grade)	CR	0.03	0.18	0.02	1.05
	Not CR	0.03	0.17		
Student is SPED (8th Grade)	CR	0.22	0.41	0.05	1.04
	Not CR	0.20	0.40		
Student was Previously LEP (8th Grade)	CR	0.05	0.22	0.09	1.25
	Not CR	0.03	0.17		
Student is LEP (8th Grade)	CR	0.09	0.28	0.09	1.15
	Not CR	0.06	0.25		
Student is Economically Disadvantaged	CR	0.80	0.40	0.00	1.00
	Not CR	0.80	0.40		
Percent of Days Absent (8th Grade)	CR	6.85	6.27	0.04	1.07
	Not CR	6.63	5.87		
Approximate Age (8th Grade)	CR	14.58	0.63	0.03	1.03
	Not CR	14.56	0.61		
Average 8th Test Score (8th Grade)	CR	-0.57	0.74	0.01	0.99
	Not CR	-0.57	0.75		
Failed a Course (8th Grade)	CR	0.41	0.49	0.11	1.03
	Not CR	0.36	0.48		
Took Remedial Course (8th Grade)	CR	0.02	0.14	0.03	1.10
	Not CR	0.02	0.13		
Took Advanced Course (8th Grade)	CR	0.14	0.34	0.00	1.00
	Not CR	0.14	0.34		
GPA (8th Grade)	CR	2.27	0.72	0.13	0.99
	Not CR	2.37	0.73		

Estimates are weighted using an inverse probability of treatment weighting to take into account matching with replacement strategy for the “Not CR” group.

Table 7: Sample Sizes By Treatment Status

		Credit Recovery	Repeat Courses
	Original Sample Size	38,282	40,300
Number of Excluded Students	Missing Demographic Data	45	108
	Missing 8^{th} Grade Covariates	4,465	5,656
	Missing 8^{th} Grade Course Information	273	283
	Matching	3,987	9,007
	Logistic Regression	110	108
	Final Sample Size	29,402	25,138

Table 8: Comparison of the Treatment and Comparison Group Samples

	Repeat Courses		Credit Recovery	
	Original Sample	Final Sample	Original Sample	Final Sample
Student is Black	0.40	0.42	0.42	0.43
Student is Hispanic	0.16	0.14	0.17	0.17
Student is Other Race	0.08	0.07	0.08	0.08
Student is Female	0.41	0.41	0.37	0.38
Student is Gifted (8th Grade)	0.05	0.04	0.03	0.03
Student is SPED (8th Grade)	0.20	0.20	0.22	0.22
Student was Previously LEP (8th Grade)	0.05	0.04	0.05	0.05
Student is LEP (8th Grade)	0.08	0.08	0.09	0.09
Student is Economically Disadvantaged	0.75	0.77	0.77	0.80
Percent Days Absent (8th Grade)	6.84	6.72	6.84	6.87
Approximate Age (8th Grade)	14.6	14.6	14.6	14.6
Average 8th Test Score (8th Grade)	-0.46	-0.50	-0.57	-0.57
Failed a Course (8^{th} Grade)	0.35	0.35	0.41	0.41
Took Remedial Course (8th Grade)	0.02	0.02	0.02	0.02
Took Advanced Course (8th Grade)	0.19	0.17	0.14	0.14
GPA (8th Grade)	2.40	2.38	2.27	2.27

Table 9: Results from Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.18***	0.58***
	(0.02)	(0.01)
Black	1.76***	0.48***
	(0.05)	(0.01)
Hispanic	1.14**	0.78***
	(0.05)	(0.04)
Other Race	1.08	0.82***
	(0.04)	(0.04)
Female	1.21***	0.93***
	(0.03)	(0.02)
Gifted in 8^{th}	0.87*	1.09
	(0.05)	(0.08)
SPED in 8^{th}	0.93**	0.88***
	(0.02)	(0.02)
Was LEP in 8^{th}	1.31***	0.66***
	(0.08)	(0.05)
LEP in 8^{th}	1.25***	0.72***
	(0.06)	(0.04)
Economically Disadvantaged	0.71***	1.35***
	(0.02)	(0.04)
Percent Absences in 8^{th}	0.92***	1.08***
	(0.00)	(0.00)
Approximate Age in 8^{th}	0.74***	1.61***
	(0.01)	(0.03)
Average Test Scores in 8^{th}	1.29***	0.80***
	(0.02)	(0.01)

Failed a Course in 8^{th}	0.78^{***}	1.22^{***}
	(0.02)	(0.03)
Remedial Courses in 8^{th}	0.66^{***}	1.17
	(0.05)	(0.10)
Accelerated Courses in 8^{th}	1.31^{***}	0.84^{***}
	(0.04)	(0.03)
GPA in 8^{th}	1.64^{***}	0.66^{***}
	(0.03)	(0.01)
Observations	57072	56974
Pseudo R^2	0.11	0.11

Exponentiated coefficients; Standard errors of logged odds in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Results from Logistic Regression with School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.60^{***}	0.59^{***}	0.68^{***}	1.18^{***}	1.17^{***}	0.99
	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)
Black	0.50^{***}			1.76^{***}		
	(0.02)			(0.06)		
Black Credit Recovery Student	0.92^{*}			1.0002		
	(0.04)			(0.04)		
Hispanic		0.84^{**}			1.12^{*}	
		(0.05)			(0.06)	
Hispanic Credit Recovery Student		0.87^{*}			1.02	
		(0.05)			(0.05)	
Economically Disadvantaged			1.48^{***}			0.63^{***}
			(0.06)			(0.02)
Economically Disadvantaged Credit Recovery Student			0.82^{***}			1.24^{***}
			(0.04)			(0.06)
Observations	56974	56974	56974	57072	57072	57072
Pseudo R^2	0.11	0.11	0.11	0.11	0.11	0.11

Exponentiated coefficients; standard errors of logged odds in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Fixed Effects Models Investigating the Association Between Credit Recovery Courses and Outcomes

	(1) Grad in Four	(2) Drop Out
Credit Recovery Student	1.30***	0.80***
	(0.05)	(0.03)
Number of Credit Recovery Courses	0.95*	0.85***
	(0.02)	(0.02)
Number of Credit Recovery Courses Squared	1.001	0.999
	(0.003)	(0.004)
Observations	57072	56974
Pseudo R^2	0.11	0.12

Exponentiated coefficients; standard errors of logged odds in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6: High School Graduation Rates by Student Race ("National Center for Education Statistics," n.d.)

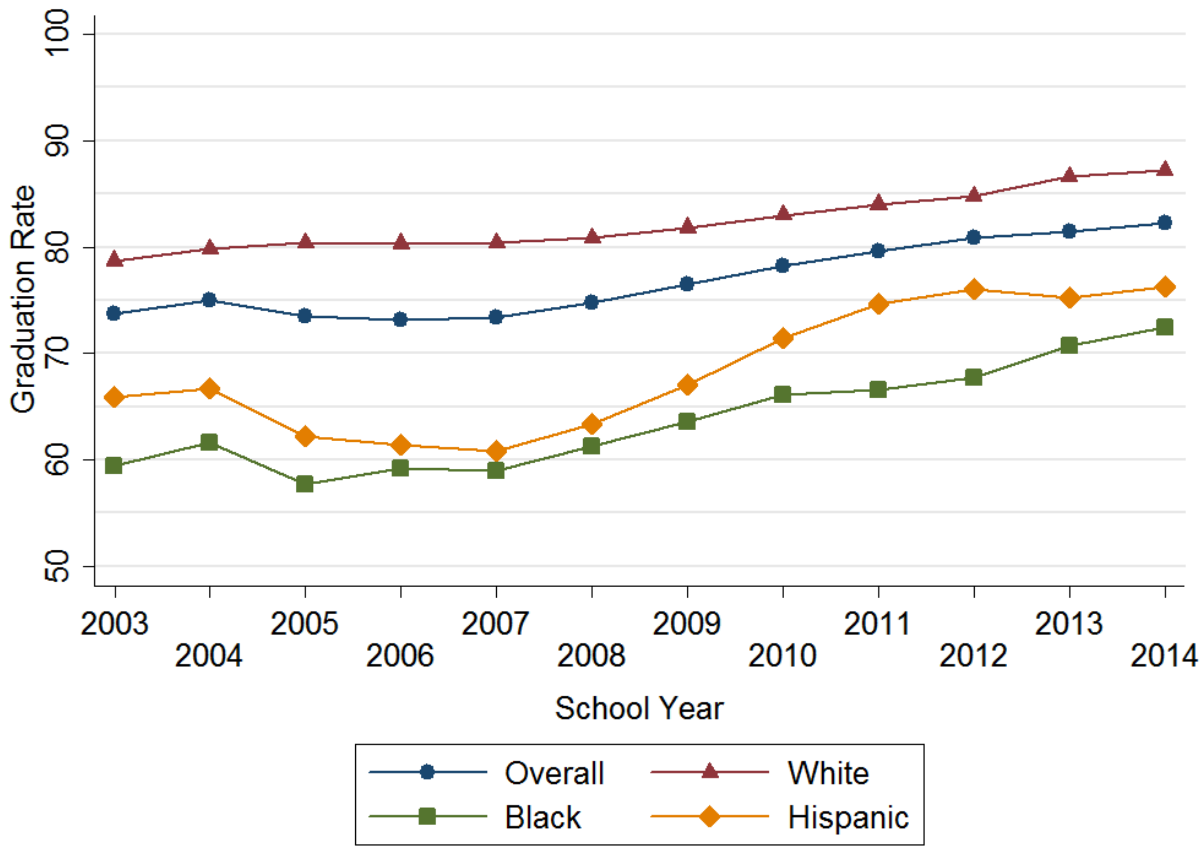


Figure 7: Status Dropout Rates by Income (“Digest of Education Statistics, 2015,” n.d.)

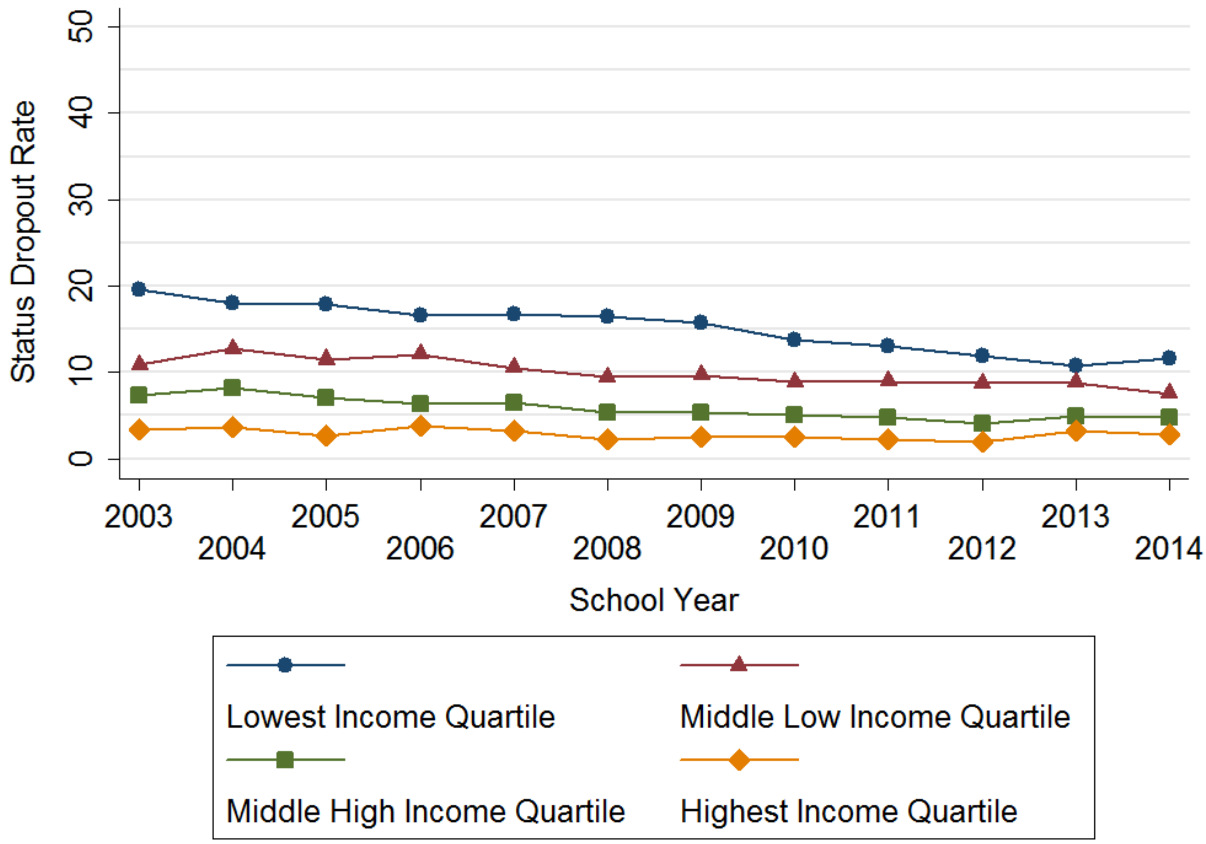
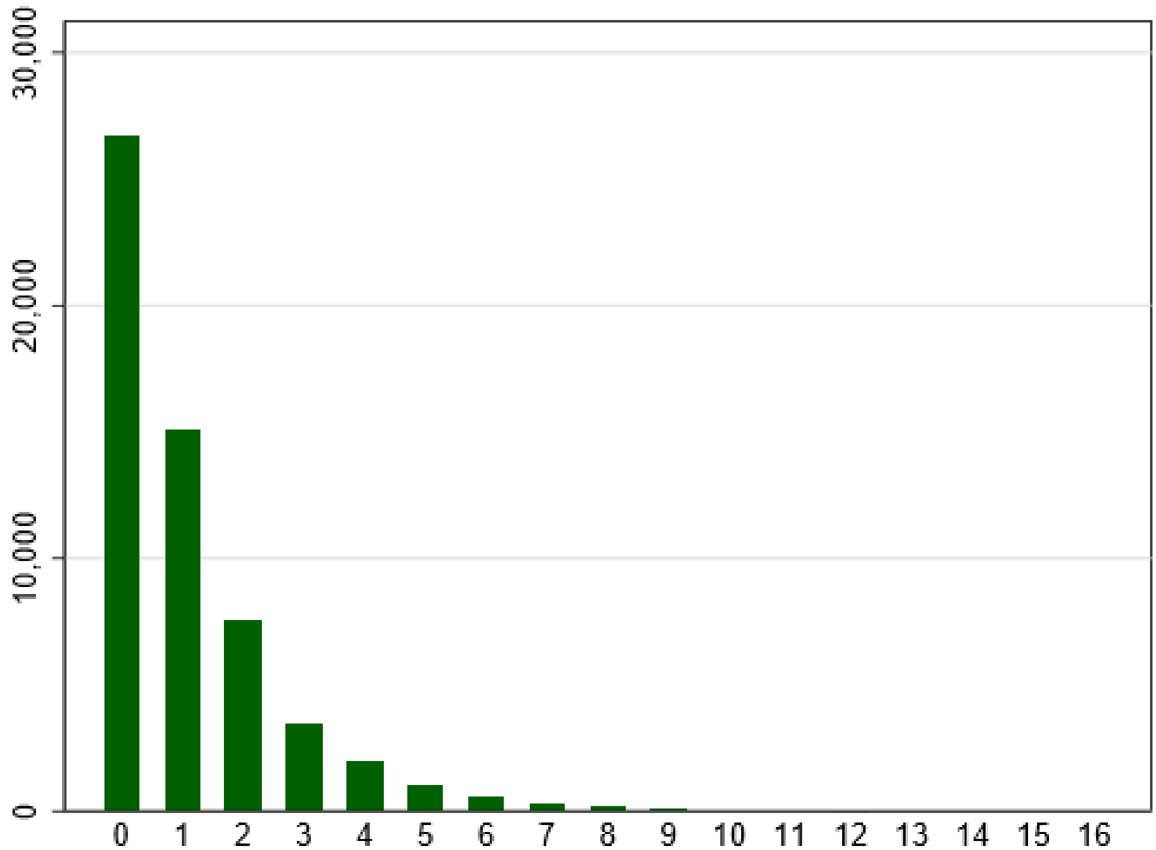


Figure 8: Number of Credit Recovery Courses Taken by Students in the Sample



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CHAPTER III

THE EFFECTS OF CREDIT RECOVERY: AN EXAMINATION OF GRADUATION RATES AND NEGATIVE SIDE EFFECTS

Introduction

In 2010-11, the U.S. Department of Education (ED) began to require high schools to report their graduation rates, and for states to hold them accountable for them ("No Child Left Behind High School Graduation Rate Non-Regulatory Guidance," 2008). At the same time, states competed for significant federal funds through Race to the Top, which offered large financial incentives to states that developed accountability systems that heavily sanctioned low-performing schools as determined by test scores and high school graduation rates ("Overview Information; Race to the Top Fund; Notice Inviting Applications for New Awards for Fiscal Year 2010; Notice," 2010). As federal-level school accountability mandates placed greater emphasis on graduation rates, states, schools, and districts have responded by offering credit recovery options along with other reforms. Credit recovery refers to online courses that students take after previously failing a traditional version of the course. Credit recovery is primarily designed as a credit accumulation intervention. Due to evidence indicating that failure to accumulate credits in a timely manner is a major barrier to high school graduation (see Allensworth & Easton, 2005; Bowers, 2010; Mac Iver & Messel, 2013), schools and districts may view credit recovery as a means to remove this barrier in response to accountability pressure to increase graduation rates. The hypothesis is that students are less likely to drop out of high school and, therefore, more likely to graduate if they can obtain credits for required courses they failed (Murin, Powell, Roberts, & Patrick, 2015; Watson, Gemin, & Ryan, 2008). Credit recovery represents a shift from the prior strategy of a student's repeating the failed course the following school year, or earning the course credit in an after school or summer school program.

Indeed, credit recovery is a very popular tool for districts and schools. In the 2009-10 school year, before the ED required that high schools be held accountable for their graduation rates, nationwide enrollment in credit recovery was estimated at over 1.1 million (Queen & Lewis, 2011). Enrollment in credit recovery courses offered through the North Carolina Virtual Public Schools increased by two thirds (from 1,923 to 3,207 enrollments) between 2008-09 and 2011-12 (Stallings et al., 2016). In North Carolina during the 2016-17 school year, 80 percent of high schools and 97 percent of school districts had at least one student enrolled in credit recovery (author's analysis). Of the estimated 80,000 high school students in North Carolina who failed a course between 2012-13 and 2016-17, 36 percent enrolled in a credit recovery course in the 2016-17 school year (author's analysis). In 2013, Connecticut became the first state to mandate that high schools offer credit recovery to all students who fail a course if the school has a dropout rate of eight percent or higher, representing a shift in the locus of decision-making about credit recovery from schools or districts to the state (Murin et al., 2015).

Despite large national enrollments, a policy mandate in Connecticut, and evidence of high utilization in at least one state, no empirical evidence indicates that credit recovery increases high school graduation rates, prevents students from dropping out of high school, or provides an educational experience equivalent to a face-to-face course (Carr, 2014; Heppen et al., 2016; Stallings et al., 2016). In fact, there are several studies that indicate that the population of students who fail courses in high school would be particularly ill-suited to succeed in an online learning environment (Viano, 2018). Students who fail courses in high school, often labeled as “at-risk students,” are more likely to have lower technological and online skills than students who do not fail courses in high school (Judge, 2005; Kuhlemeier & Hemker, 2007; Oliver, Osborne, Patel, & Kleiman, 2009; Valadez & Duran, 2007). Also, students who fail one class are more likely to have failed other courses as well, perhaps indicating multiple skill deficits that could make it challenging to succeed on a complicated online platform (Bowers & Sprott, 2012; Judge, 2005; Roderick, 1994). As summed up by Huett and colleagues in a review of knowledge about K-12 online learning, “We fear that distance education may become little more than a 'dumping ground' for credit recovery...the exact opposite population the research says tends to thrive in the distance environment” (Huett, Moller, Foshay, & Coleman, 2008, p. 64). While schools across the country are turning to credit recovery as a way for students to earn course credits, there are significant reasons to doubt that an online learning approach would be successful with the population of students who fail courses in high school.

Furthermore, the negative effects of interventions designed to quickly meet accountability targets are well documented (see Balfanz, Legters, West, & Weber, 2007; Dee, Jacob, & Schwartz, 2013; Jennings & Bearak, 2014). As an intervention implemented to respond to federal accountability pressure to increase high school graduation rates, credit recovery has the potential to introduce unintended negative side-effects, such as increased course failure rates, lower test scores, increased absences, and higher dropout rates. For instance, students could respond to the widespread availability of credit recovery by failing courses the first time if they prefer to spend time during the school day in credit recovery, which allows them to be on the internet. In fact, one ethnographic study found that students are spending significant amounts of time during credit recovery courses on other internet sites (Ingerham, 2012). In addition, teachers at schools with credit recovery programs might be more likely to withhold the extra effort to assist low-performing students, thereby allowing more of them to fail, since the teacher knows the student can make up the credit through credit recovery. Students who take several credit recovery courses might feel less connected to school, since they no longer have specific teachers to whom they are reporting for class, thus leading to higher absence rates. These higher course failure and absence rates could lead to higher dropout rates, since course failure is associated with dropping out of high school (Allensworth & Easton, 2005; Barrington & Hendricks, 1989; Mac Iver & Messel, 2013; Silver, Saunders, & Zarate, 2008). Also, credit recovery could lead to lower end-of-course exam scores if credit recovery courses are of low-quality, and/or students learn less in credit recovery courses than if they had repeated the face-to-face version. Evidence indicates that students gain proficiency by repeating courses in full when they previously failed in a traditional setting (Fong, Jaquet, & Finkelstein, 2014), but we know little about the effects of credit recovery on student learning.

Due to the widespread popularity of credit recovery, investigating both the potential benefits and negative side-effects of credit recovery will be imperative to determining whether it is an effective strategy for schools to implement in order to boost graduation rates, or an approach that leads to barriers to student learning and degree attainment. I investigated the following research questions: (1) To what extent does introducing credit recovery options at the school-level relate to the graduation rate, the dropout rate of students, or rates of passing previously failed courses in those schools? (2) To what extent is offering credit recovery associated with higher face-to-face course failure rates, higher absence rates, and lower proficiency rates on the end-of-course exams?

Below, I review prior literature on interventions meant to increase the high school graduation rate, as well as the data and methods of this study, its limitations, and its potential contributions. Results indicate that credit recovery implementation leads to lower high school graduation rates and lower test scores, and high levels of credit recovery enrollment are associated with higher course failure rates and higher passing rates of previously failed courses.

Policy Tools and Programs Available to High Schools to Increase Graduation Rates

When faced with external pressure to increase graduation rates, districts and schools are confronted by a complicated landscape of research on how to effectively reduce the dropout rate and increase the graduation rate. In this section, I present an overview of the different programs that schools have turned to in the past to increase graduation rates, along with the efficacy of these approaches. First, I review dropout prevention programs that have been shown to be effective using randomized control trials (RCTs) or quasi-experimental designs. Second, I review programs, some of which are extremely popular at the national level, that have limited evidence on their effectiveness in increasing high school graduation rates. The third type of study reviewed here is systematic reviews on dropout prevention programs. Overall, the confusing literature base of mixed findings on popular high school graduation intervention programs could lead school and district administrators to seek to identify new but understudied dropout prevention strategies, such as credit recovery.

Three programs designed to reduce dropout rates have been shown to be at least somewhat effective in randomized trials, including the Teen Outreach program (Allen, Philliber, Herrling, & Kuperminc, 1997), the Peer Connections Program for male students only (Johnson, Simon, & Mun, 2014), and Career Academies (school within a school model) (Kemple and Snipes, 2000). However, a follow-up study on Career Academies, which gives students eight years to complete high school, did not find statistically significant results on high school completion, perhaps because the authors chose to include earning a GED as an equivalent to completing high school, despite ample evidence that a GED is not equivalent to a high school diploma (Kemple & Willner, 2008).

Other studies use quasi-experimental methods to show evidence of the efficacy of dropout prevention programs. In Chicago Public Schools in the early 2000s, lower performing ninth-grade students who were assigned to a “double dose” of Algebra I were more likely to graduate from high school than students who were just above the cutoff score on their eighth grade math test (Cortes, Goodman, & Nomi, 2015). In addition, Saavedra (2014) found that participation in the International Baccalaureate program in Chicago Public Schools is associated with an increased probability of graduating from high school. Many other correlational studies find evidence that student engagement, teacher-student relationships, school-based health center use, academic tutoring, less punitive classroom management, and relevant and challenging coursework are all associated with a lower risk of high school dropout and/or higher rates of high school graduation (Fall & Roberts, 2012; Finn & Rock, 1997; Kerns et al., 2011; Lee & Burkam, 2003; Mayer et al., 1993; Pearson & Banerji, 1993; Somers & Piliawsky, 2004).

One very popular dropout reduction program, AVID, which has implemented in more than 5,700 schools across the country in the 2015-16 school year (“Where is AVID?,” n.d.), has been evaluated in Texas, where researchers found that AVID high schools have higher graduation rates and higher graduation rate growth over the study period (Watt, Powell, Mendiola, & Cossio, 2006). However, little additional evidence sheds light on its efficacy using quasi-experimental or experimental designs.

Several studies have shown that popular interventions schools have used over the last two decades might not be as effective as program implementers had hoped. Evaluations of the Check

& Connect program (Evelo, Sinclair, Hurley, Christenson, & Thurlow, 1996) have found positive effects for students progressing in school, but no evidence that Check & Connect led to higher graduation rates (U.S. Department of Education, Institute of Education Sciences, What Works Clearinghouse, 2015). In an evaluation of a dropout prevention program specifically designed according to recommendations from an IES practice guide on how to decrease high school dropout rates, including assigning an adult advocate to at-risk students for academic support and enrichment (Dynarski et al., 2008), there were no significant program effects on high school graduation rates (Mac Iver, 2011). Another intervention, Project Graduation Really Achieves Dreams (Project GRAD), is a school-wide intervention in elementary, middle, and high schools that enroll predominately low-income student populations. A randomized control trial found no significant effects of program participation on high school graduation probabilities (Snipes, Holton, Doolittle, & Sztejnberg, 2006). With many disappointing evaluation findings from programs that were thought to be very effective at increasing graduation rates, school and district leaders ought to be dubious of popular programs that make big claims about dropout prevention strategies.

Another policy designed to increase graduation rates and decrease dropout rates is implementing a “no-zero” approach to grading. This policy, at its most extreme, requires all teachers to enter a passing grade for all assignments, regardless of whether the student completed the assignment, or the quality of the completed assignment. However, this policy can also refer to a general sentiment that students should be given multiple chances to complete or revise an assignment before being given a low grade. No-zero policies are being implemented in schools and districts across the country with the intent of incenting students to stay in school and to make them more likely to earn the credits necessary to graduate (Balingit & George, 2016; Walker, 2016). Despite the popularity of this policy, no evaluations have investigated no-zero policies for their effectiveness at decreasing dropout rates or increasing graduation rates.

Two systematic reviews of the literature on dropout prevention programs have found nearly opposite results. A systematic review of the literature on dropout prevention from 2003 found that there is no one particular best practice or beneficial treatment available to increase graduation rates (Prevatt & Kelly, 2003). However, a systematic review of the literature on dropout prevention from 2011 found that, overall, dropout prevention programs are effective at reducing dropout and increasing school completion. This meta-analysis estimates that, across studies, the average dropout rate for the control group was 21 percent, with the treatment group average of 13 percent (Wilson, Tanner-Smith, Lipsey, Steinka-Fry, & Morrison, 2011). When faced with a decision on how to improve graduation rates, which do district and school officials believe: that no existing program works, or, on average, that all existing programs work?

Overall, the evidence on dropout prevention programs is mixed, with some popular programs lacking a clear evidentiary base on their effectiveness. Some of the well-researched, effective programs are costly and difficult to implement (i.e., Career Academies, International Baccalaureate), or are not specific interventions that schools can easily implement with fidelity (i.e., socio-emotional learning programs, increasing student engagement). Within this framework, credit recovery offers an option that is relatively easy and inexpensive to implement in schools with computers and high-speed internet access. In addition, credit recovery directly addresses a specific cause of school dropout: low credit accumulation. With schools turning to credit recovery in response to new federal accountability targets, this study investigates whether the adoption of credit recovery at the school or district level was an effective intervention for increasing graduation rates and/or decreasing dropout rates.

Potential Unintended Consequences of Dropout Prevention Programs

Programs intended to increase graduation rates and decrease school dropout can also lead to negative effects unanticipated by program developers and implementers. For instance, an earlier study of the double dose Algebra I program in Chicago Public Schools found that increased Algebra I tracking (due to students in the double dose condition being placed in classes together) led to declines in course grades of students not in the treatment condition (Nomi & Allensworth, 2009). In a study of intensive group counseling of at-risk students, the researcher found that treatment students had higher dropout rates as compared to non-treated at-risk students (Catterall, 1987).

Several studies have investigated the unintended consequences of the accountability reforms in the No Child Left Behind Act of 2001 (NCLB). Balfanz and colleagues (2007) report on the contradictory finding that low-performing high schools that are improving their academic performance are still being sanctioned under NCLB, while similar high schools that are not improving as much do not face sanctions. One difference between similar high schools that do or do not make adequate yearly progress (AYP) is that high schools with more subgroup accountability targets are less likely to reach AYP than high schools with fewer subgroups. Since AYP status determines school sanctions under NCLB, the findings from this paper indicate that more diverse schools might face more accountability sanctions than less diverse schools (Balfanz et al., 2007). Dee and colleagues (2013) investigated instructional time before and after NCLB, finding that schools reallocated time away from science and social studies after NCLB, devoting that time to reading. Jennings and Bearak (2014) investigated the extent to which the emphasis of some state standards on high-stakes tests led to changes in teachers' instructional strategies, finding that they tended to focus more on standards that were heavily weighted on the tests, to the detriment of the amount of time spent on instruction based on other standards. With these kinds of unintended consequences in mind, this study also explores whether offering credit recovery courses leads to lowered incentives for students to pass courses the first time, higher dropout rates, lower proficiency rates on end-of-course exams, and more absences.

Credit Recovery as an Intervention to Increase Graduation Rates

This study represents the first known attempt to quantify the impact of offering credit recovery at the school-level on school-level outcomes, such as high school graduation rates and exam proficiency rates. One previous study uses data from North Carolina to investigate the effectiveness of credit recovery on students' probabilities of graduating from high school. The previous study used data from the 2008-09 through 2011-12 school years for credit recovery courses taken through the North Carolina Virtual Public School (NCVPS). The authors found that, when comparing students who take online credit recovery to students who repeat courses for credit in a traditional classroom, credit recovery students are slightly less likely to graduate from high school overall, and slightly more likely to graduate within four years (Stallings et al., 2016). The current study is distinguished from the prior study in several respects. First, this study includes credit recovery courses taken through private providers as well as through the North Carolina Virtual Public School. Second, this study is based on more recent time data (2012-13 through 2016-17), which adds to the policy relevance of the findings. Third, this paper uses sophisticated causal inference methods that attempt to isolate the causal effect of credit recovery on schools. Below, I review the data, sample, and empirical framework for this study to assess the effectiveness of credit recovery as a school-level intervention to increase high school graduation rates and decrease dropout rates.

Data and Sample

The data for this project comes from an administrative database maintained by the Education Policy Initiative at the University of North Carolina at Chapel Hill (EPIC). The database includes comprehensive student and school-level records for all public schools in North Carolina. Student course roster files and student grade records are particularly important data files for this project, as these files identify schools that enroll students in credit recovery. The specific data files I will access for this essay include student course roster and grade files, school demographics, and school performance files.

The units of analysis for this paper are schools. For this study, credit recovery enrollment is restricted to core courses required to graduate from high school. Core subjects include English, science, social studies, and math. Required courses refer to the official graduation requirements for each core subject (see "High School Graduation Requirements," n.d.).[8]

This study focuses on core, required courses for two reasons. First, if credit recovery courses were specifically implemented in order to raise graduation rates, then, theoretically, the impact of offering credit recovery would be concentrated among the courses that address graduation requirements. The second reason is practical. Students enroll in thousands of unique courses annually, and the credit recovery identification process (explicated below) involves identifying individual courses. Identifying all courses that students enroll in regardless of their utility in determining whether or not a student graduates from high school would be extremely time consuming and not directly related to the likely mechanisms through which credit recovery would impact high school graduation rates. At this time, schools with credit recovery options can

[8] Regardless of year or track, students are required to complete four years of English, at least three math courses, Biology with at least one other science course, and at least two social studies courses. Go to http://www.ncpublicschools.org/docs/curriculum/home/graduationrequirements.pdf for more information.

be identified between 2012-13 and 2016-17 due to limited availability of course grade files used in credit recovery identification (described below). Depending on the specification, the sample of schools is either from between 2012-13 through 2016-17, or 2004-05 through 2016-17.

There are approximately 600 schools with high-school-level grades in North Carolina. Most of the 400 schools are traditional high schools with grades 9-12, while the other 200 contain other grades in addition to 9-12 ("Facts and Figures 2015-16," 2016). Approximately 47 percent of the high schools are rural, and 22 percent of high schools are in cities (author's analysis). The schools' racial makeup ranges from being 100 percent white to 99 percent non-white, with the median across all high schools being 54 percent white students, 28 percent black students, and 12 percent Hispanic students. The percentage of economically disadvantaged students ranges from zero to 100 percent, with the median school having half of the student body classified as economically disadvantaged. Overall, North Carolina contains a large number of high schools that are located in a diverse array of settings by urbanicity, racial makeup, and socioeconomic status.

Schools in North Carolina have two options for credit recovery: the publically-run North Carolina Virtual Public School (NCVPS), or privately-run providers of online courses. This is a very common configuration of credit recovery options across the country, where at least 40 states have a state-run virtual school, and privately provided courses are offered ubiquitously (Watson, Gemin, & Ryan, 2008). NCVPS courses are available across the state, and schools pay individually for each student enrolled, with fees ranging from $235 for a summer class to $438 for a year-long class ("North Carolina Virtual Public School," n.d.). Alternatively, private providers of online course content can have contracts with schools and districts to provide credit recovery courses. Schools and districts can offer privately-provided courses as long as they appear on an "Approved Vendor Courses" list maintained by the NCVPS.[9] Course vendors that wish to have contracts with schools in North Carolina submit individual courses for approval, and courses are assessed based on rubric for both course and teacher quality ("North Carolina Virtual Public School," n.d.).

Measures

Credit Recovery Schools

Treatment in this study is defined as enrolling students in credit recovery for core, required courses. To define the treated members of the sample, I examined the student-level files to identify credit recovery enrolled students and the schools in which they were enrolled. Identifying whether a student is enrolled in a credit recovery course is based on several source variables, including course codes, NCVPS records, and course titles. Because no single variable or procedure can identify all credit recovery courses, I followed a multistep process to identify credit recovery courses and students enrolled in those courses. The North Carolina Department of Public Instruction (DPI) provides a specific course code for schools to use with credit recovery courses, helping to identify many of the students enrolled in credit recovery. However, not all schools comply with the use of this course code. The noncompliance with the credit recovery course code specification is clear in the data files when examining course titles, many of which include the phrase "credit recovery," but are not identified as such through the course code. The noncompliance with the course code specification has been confirmed by other researchers who have worked with DPI on credit recovery course identification (Weiss &

[9] NCVPS no longer maintains the Approved Vendor course list as of 2017, but took on this role for all years of data for this study.

Stallings, 2015). In order to identify as many credit recovery courses as possible, I investigated course titles, previous courses that students failed, and course codes. I also identified credit recovery courses by identifying whether a student failed a course in a previous year or the current school year and retook the course online.

This study explores several ways of measuring the dosage of credit recovery in schools. Including schools with very low enrollments of students in credit recovery might dilute the treatment effect if the effects of credit recovery are only realized at a certain threshold enrollment rate. Additionally, measures indicating the dosage of credit recovery in the school can help to define an appropriate comparison group, as further explained below. Dosage is explored in multiple ways. First, treatment is defined by the percentage of students in the school who enroll in at least one credit recovery course. This measures the student body's exposure to credit recovery courses. Second, treatment is defined as the percentage of students who failed a core, required course in the school, and who are now enrolled in credit recovery. This second measure does not indicate how widespread credit recovery use is across the school, but is instead a measure of how often a school assigns credit recovery to the target population for it; i.e., students who lost course credit. These measures are not sensitive to the potential difference between schools that tend to enroll students in very few credit recovery courses versus schools with higher credit recovery course loads. The third measure is the percentage of course enrollments in the school that are credit recovery courses only for courses with associated end-of-course exams (i.e., Math I, Biology, and English II). Restricting the percentage to include only end-of-course exam courses provides a more proximal measure of enrollment in courses that are tied to end-of-course exam proficiency rates.

Dependent Variables

The study includes six dependent variables: graduation rates, dropout rates, course failure rates, end-of-course exam proficiency rates, chronic absenteeism percentage, and the passing rate of previously failed courses. Graduation rates are the state's official four-year cohort graduation rate, indicating the percentage of first-time ninth graders who graduate within four years. The dropout rate indicates the percentage of students who dropped out of school in the given year.[10] At the student-level, dropping out is indicated by a student who was enrolled in a previous school year, but is no longer enrolled in any school in North Carolina the following school year and is not receiving a high school credential. The end-of-course exam (EOC) proficiency rate is the percentage of students in the school who scored proficiently on the Math I, Biology, and English II end-of-course exams.[11,12] For accountability purposes, schools often use an overall proficiency rate, labeled "the performance composite," which includes end-of-grade exams at the

[10] Most schools that had less than five and greater than zero dropouts in the 2008-09 school year are excluded from analysis because the state suppressed these dropout count values in that school year only (about 50 schools).

[11] Due to suppressed data, this variable was calculated using student-level files as opposed to using a publicly available version of the EOC performance composite. The numerator includes the number of tests on which a student scored proficiently within a school year (i.e., a student is counted twice if they scored proficient on two EOCs in one year). The denominator includes the values of the numerator added to the number of EOC exams taken by students that did not result in a proficient score. Other decision rules included in the publicly-available EOC performance composite were not included here. For instance, high schools were not given credit if their students had passed an EOC exam in eighth grade.

[12] Math I, Biology, and English II have been the only EOC exams since the 2011-12 school year. Before this school year, students also took EOC exams in Algebra II, Civics & Economics, Physical Science, U.S. History, Math II (Geometry), Chemistry, and Physics. Prior to the 2010-11 school year, students needed to score at an achievement level three or above on the EOC exams for Math I (Algebra I), English I, Biology, U.S. History, and Civics & Economics in order to graduate from high school. No documented changes in the requirements occurred during the treatment years (2014-2017), although these changes in EOC exam regulations could affect prior year trends.

elementary and middle school levels. However, this study focuses on high-school-level courses only, so I utilized the proficiency rates for EOCs only.

The course failure rate indicates the percentage of student enrollments that are associated with a course failure for first-time enrollments only. This rate will be calculated by finding the number of course enrollments in core, required subjects that are first-time enrollments—excluding students who are repeating the course—and finding the number of these enrollments associated with a failing grade. Since the process of identifying first-time course enrollment includes using grade files, the course failure rate variable is not available prior to the 2012-13 school year. These same files are utilized to create the passing rate of previously failed courses. This variable represents the number of core courses that students passed after failing in the current or previous school year over the number of core courses the students in the school failed in the current or previous year.[13] The chronic absenteeism percentage is the percentage of students in the school who were absent for 15 or more days ("Chronic Absenteeism in the Nation's Schools," 2016).

Empirical Framework

This empirical framework is designed to estimate the extent to which credit recovery options at the school-level are associated with both positive benefits, such as higher high school graduation rates, as well as unintended consequences, such as higher course failure rates. The ideal framework for making a causal inference about the effects of credit recovery on schools would be to randomly assign high schools to offer credit recovery or forego it. As most high schools at this point have already adopted credit recovery, this random assignment strategy is not

[13] The denominator does not include core courses that were failed and then passed in a previous school year.

a practical option. In order to attempt to make causal inferences, this study used a comparative interrupted time series (CITS) quasi-experimental design. This method is helpful because simply comparing post-treatment mean differences between the treatment and comparison groups (i.e., as is done with a randomized control trial) could lead to biased results if the treatment and comparison groups differed prior to treatment, or if the comparison group experienced some change in outcome over time unrelated to their treatment status.

CITS is designed to address several sources of bias that can manifest when simply comparing post-treatment differences between the treatment and comparison groups. The basic assumption of the CITS model is that both treatment and control schools would continue their pre-trends into the post-treatment period in the absence of the introduction of credit recovery in the treatment schools (conditional on covariates). CITS controls for trends in the outcome for the comparison group as well as in pre-treatment trends for the treatment group (Somers, Zhu, Jacob, & Bloom, 2013). Next, CITS estimates the treatment effect by isolating deviations from the trend in the outcome for the treatment group.

The major challenge of estimating the causal effect of credit recovery on schools is that in the first year for which data are available, 2012-13, 81 percent of schools already offered credit recovery. For these schools, the years in which they began offering recovery are unknown. Therefore, the "treatment" group for the CITS estimates will be the schools that implemented credit recovery between 2013-14 and 2016-17; i.e., 73 schools across the state. (See Table 12 for a count of schools with credit recovery and schools without credit recovery across the timeframe when data is available on credit recovery enrollment.) In another study using CITS to estimate program effects, specifically trying to quantify the impact of No Child Left Behind (NCLB) on student achievement, Dee and Jacob (2011) defined the treatment group as U.S. states that had no prior accountability system, and the comparison group as states that had an accountability system prior to NCLB. The underlying hypothesis is that NCLB would represent a change for states without accountability systems, while having little discernable difference in policy from states with accountability systems (Dee & Jacob, 2011). Other studies have followed this approach (e.g., Grissom, Nicholson-Crotty, & Harrington, 2014), and I take a similar one, given that 81 percent of schools had credit recovery in 2013 (the first year of course file data). I define the treatment group as schools that implemented credit recovery in 2014, 2015, 2016, or 2017, since the year those schools implemented credit recovery is known.

Initially, I defined all schools that previously implemented credit recovery as the comparison group. I then examined various subsamples of that comparison group, described below, to remove threats to the validity of using the entire comparison group. The first approach to estimating the effects of credit recovery implementation relies on the assumption that late implementers of credit recovery are experiencing a change, while earlier adopters are not. However, if the use of credit recovery was increasing or decreasing in the earlier implementers, the outcomes may be affected by credit recovery enrollment changes. Therefore, I found subsamples of earlier credit-recovery-implementing schools that have had little variation in the extent to which credit recovery was used during the pre-2014 period. After exploring several different definitions of what it means to have little variation in credit recovery enrollments over time, my final version indicates that schools did not increase their credit recovery enrollment by more than a standard deviation on any of the three-credit recovery enrollment measures described above. Results were qualitatively similar, regardless of the measure of stability of credit recovery enrollment.

Validity Checks

I performed several validity checks based on the advice of Angrist and Pischke (2009) in order to assess whether key assumptions of the CITS model were met, and whether the treatment effects can be reasonably interpreted as causal. The basic assumption of the CITS model is that treatment and comparison schools would continue to move along their trends from the pre-treatment into the post-treatment period, in absence of the introduction of credit recovery in the treatment schools, ceteris paribus. The validity of this can be partially checked by examining the *parallel trends assumption*. In order to check the plausibility of the parallel trends assumption holding under these models, I graphically investigated pre-intervention trends for the outcome variables between the treated and comparison schools. In order to implement this test (considering there are different baseline years for the credit recovery treatment), I centered the year variable based on the first year of treatment by school. This test used the baseline model (below) with the *year* variable on the x-axis, and the outcome on the y-axis. All treatment schools will have a value of zero for the *year* variable in the year prior to treatment, with a value of one for the first year of credit recovery implementation. For more than one year prior to treatment, the *year* variable will have negative values, such that two years prior to treatment, the *year* variable will have a value of negative one. For comparison schools, the *year* variable will be centered on the same year as the first year of treatment for the first cohort of schools to implement credit recovery. While CITS explicitly models prior trends, it is important to examine the trends to see whether they cross or are diverging prior to the implementation of credit recovery.

The second validity check examines whether differences in the outcomes occurred prior to credit recovery implementation—i.e., the *Granger* test. In this case, the Granger test assesses whether the outcomes in the treatment schools appear to change before credit recovery was introduced. Ideally, outcomes would only change in response to (temporally after) the treatment, not before the treatment occurs. To perform the Granger test, the model will be updated to include indicators of the two years prior to treatment interacted with treatment indicators. The coefficients on these pre-treatment trend variables not being statistically significant indicate that the model passes the Granger test (Angrist & Pischke, 2009). Passing these validity checks bolsters the claim that the CITS estimates are causal, since the data conforms to the parallel assumption.

The third validity check is to assess whether or not the treatment schools and comparison schools are balanced on observable covariates. If the treatment and comparison schools are significantly and substantively different from one another, it calls into question the validity of the comparison schools as a strong counterfactual for the treatment schools. Covariate balance will be assessed based on the number of enrolled students, school urbanicity, school funding, and the percentage of students by race/ethnicity, limited English proficiency status, special education status, gifted status, and economically disadvantaged status.

Model Specifications

The main specification of the CITS model will include the sample of schools from 2004-05 through 2016-17.[14] The model would be estimated using the following equation:

$$(1)\ y_{st} = \beta_0 + \beta_1 (Year - 2013)_t + \beta_2 (Year - 2013)_t \times CRSchool(after2013)_s +$$

$$\beta_3 Year2014_t + \beta_4 Year2014_t \times CRSchoolin2014no2013_s +$$

[14] Data on the EOC proficient rate and the four-year cohort graduation rate are unavailable for 2004-05, so these models include the years 2005-06 through 2016-17. Data on the dropout rate are not yet available for the 2016-17 school year, so those models only include the 2004-05 through 2015-16 school years.

$$\beta_5 Year2015_t + \beta_6 Year2015_t \times CRSchoolin2015no2013_s +$$

$$\beta_7 Year2016_t + \beta_8 Year2016_t \times CRSchoolin2016no2013_s +$$

$$\beta_9 Year2017_t + \beta_{10} Year2017_t \times CRSchoolin2017no2013_s + \boldsymbol{X_{st}\lambda_k} + \delta_s + \varepsilon_{st}$$

where y_{st} is the outcome for school *s* at time *t*, representing either graduation rates, dropout rates, EOC proficiency rates, or the chronic absenteeism rate. Dropout rates are not available at this time for the 2016-17 school year, so the coefficients for the 2017-related variables drop out in models with the dropout rate as the dependent variable. I also estimated models where the outcomes are the core course failure rate and the passing rate of previously failed courses. However, the models with these outcomes only have data available from 2012-13 through 2016-17. These models are difference-in-differences, not CITS models with 2012-13 as the pre-intervention year. A vector of controls, $\boldsymbol{X_{st}}$, is included to control for time-varying school characteristics. These covariates include the number of enrolled students, the percentage of students by race/ethnicity, limited English proficiency status, special education status, gifted status, and economically disadvantaged status. The δ_s variable represents a school fixed effect, and ε_{st} is the error term.

The variable indicating the year is centered on the first year of treatment, 2013, and included to account for the trend in the outcome over time for the comparison group. The interaction $(Year - 2013)_t \times CRSchool(after2013)_s$ represents the trend for the treatment group. Deviations from the overall trend are estimated by treatment year (2014, 2015, 2016, and 2017) and by treatment status. The four covariates, $Year2014_t,\ Year2015_t,\ Year2016_t,$ $Year2017_t$, represent the deviations from the year trend for the comparison schools in those years. The interactions between the covariates $Year2014_t, Year2015_t, Year2016_t, Year2017_t$ and the indicators of being a *CRSchool* represent the treatment effects by year. For the 2014 school year, the total treatment effect is the β_4 coefficient, representing the within-school deviation for the schools who implemented credit recovery in 2014, plus the β_2 coefficient, since this coefficient represents the effect of a one-year change for the treatment group. For the 2015 school year, the total treatment effect is the β_6 coefficient, representing the within-school deviation for schools who implemented credit recovery in 2014 or 2015, plus two times the β_2 coefficient. For the 2016 school year, the total treatment effect is β_8 plus three times β_2. For the 2017 school year, the total treatment effect is β_{10} plus four times β_2.

Dosage of Credit Recovery

Following the estimation of a plausible causal effect of credit recovery, an analysis of the association between different measures of the extent of credit recovery use (dosage) and the outcomes of interest is conducted. If the effects of implementing credit recovery are causal, then changing the dosage of credit recovery in a school would be expected to lead to increases/decreases of the outcomes in the direction of the causal effects. However, unlike the CITS model, the results from the following specification are intended to be descriptive. I am not isolating exogenous changes in credit recovery enrollment to establish causality. These models are meant to be interpreted descriptively.

Model (2) estimates the association between credit recovery dosage and the six outcomes of interest:

$$(2)\ \ y_{st} = \beta_0 + \beta_1 PercCR_{st} + \beta_2 PercCR_{st}^2 + \boldsymbol{X_{st}\beta_k} + \delta_s + \gamma_t + \varepsilon_{st}$$

The variable $PercCR_{st}$ represents one of the three credit recovery dosage measures discussed above. A quadratic term of this variable is included, as F tests indicate on several models that the relationship between credit recovery usage and the outcomes is non-linear. These models exploit changes over time within schools in their levels of credit recovery enrollment (due to the school and year fixed effects, which subtract the group mean of each variable in the model), where β_1 and β_2 represent the predicted change in the outcome for each percentage increase in the measure of credit recovery proliferation. All schools are included in this sample, regardless of credit recovery implementation. As shown in Figure 9, schools on average increased credit recovery enrollments, using the three measures of enrollment over this time period. In order to distinguish these changes from an annual trend, a year fixed effect, γ_t, is added.

Limitations

This study has three major limitations to note. First, the validity of the CITS empirical framework is reliant on the plausibility of the basic assumptions of those models. I test the plausibility of the parallel trend assumption by examining pre-intervention trends, but there are no validation tests that can truly rule out the possibility that differences in outcomes are due to the differences that would have occurred in the absence of treatment. These limitations are risks inherent to the use of the CITS model and are not unique to this study in particular.

Second, the CITS strategy is unable to identify the causal effect of credit recovery implementation relative to no credit recovery because of a lack of data in years prior to 2013. Most schools already offered credit recovery in 2012-13, and the year they initially implemented credit recovery is unknown. The first credit recovery courses could have been offered in the early 2000s, but the data is not available that would make it possible to track courses and course grades prior to 2012-13. This lack of data represents a major limitation of this study as the majority of schools already had a credit recovery option in 2012-13. Without knowing when these schools adopted credit recovery, it is difficult to know the causal effect of implementing credit recovery at all school sites, thus leaving the estimates in this project as estimating the effect of late adoption of credit recovery.

The third limitation has to do with data manipulation. As with all secondary datasets, researchers are reliant on those collecting, inputting, and cleaning the data to do so accurately. For instance, students' final grades are not supposed to be deleted during this time period. If a student retakes a course for credit (i.e., non-credit recovery), their failing grade is supposed to be "suppressed" from their record for transcript and GPA purposes, but not deleted from the administrative records used for this study. However, it is possible that someone inputting the data did not comply with this rule, and instead simply deleted the failing grade, leaving no record of a student's failing a course. This kind of data manipulation will only be an issue in this study to the extent that manipulation patterns are correlated with the outcomes. For instance, if non-compliance with rules about entering grades was indicative of overall mismanagement in the school, the school would be low performing while also suppressing credit recovery enrollment. If manipulation occurs randomly across schools, then it will not bias the results.

Results

The results from the CITS model are in Tables 13-18. The dependent variables are all standardized by year to have a mean of zero and a standard deviation of one for each year of data. Table 13 lists the results for models with the high school graduation rate dependent variable. Results are very similar using both comparison groups. Excluding schools with credit recovery in 2013, schools with credit recovery in 2015 and 2017 are predicted to have lower high school graduation rates by a fifth to half of a standard deviation. The coefficients on having credit recovery in 2014 and 2016 (excluding schools with credit recovery in 2013) are negative, but not statistically significant. These results indicate that implementing credit recovery leads to a significantly lower high school graduation rate. The year trend for the treatment schools is positive and not statistically significant. Because the year trend for the treatment groups has a small coefficient (0.02), the overall positively signed trend does not significantly diminish the negative treatment effects for the 2015 and 2017 years. For instance, the cumulative effect of credit recovery implementation by 2017 for schools implementing credit recovery in 2014 is predicted to be about a third of a standard deviation decrease, which is equivalent to an eight percentage point (or a ten percent) lower high school graduation rate.

Table 14 shows the results for running the CITS model using the passing rate of a previously failed courses dependent variable, keeping in mind that this model does not include enough data prior to treatment to establish trends. The coefficients on the treatment variables are statistically insignificant, positively signed, and increase in size over time. By 2017, the coefficients are quite large, approaching one standard deviation, but the estimates are imprecise. The year trend for the treatment groups has a negative, statistically insignificant coefficient. Taking into account the year trend and 2017 treatment effect, the total association between credit recovery implementation in 2014 and the outcome by 2017 is about a half a standard deviation in size, but is also not statistically significant.

In Table 15, the dependent variable is the dropout rate. Results for the dropout rate dependent variable differ based on the comparison group. When the comparison group is all high schools that had credit recovery prior to 2014, the results are positively signed and statistically significant for all three years of treatment (2017 data is unavailable at this time). However, when the comparison group is comprised of schools that maintained stable levels of credit recovery enrollment between 2013 and 2017, the coefficients are reduced to almost zero and are no longer statistically significant. This differing result indicates that, while the effect of credit recovery on the treatment group in column (1) appeared to indicate that credit recovery implementation led to higher dropout rates, these effects could have been due to changing credit recovery enrollment behavior in the comparison group. The portion of the comparison group that was greatly increasing or decreasing their credit recovery enrollment also had decreasing dropout rates, leading to the misleading result. The year trend is stable across groups in that it remains small (0.01) and statistically insignificant.

The results for the chronic absenteeism rate are listed in Table 16. Just as with the dropout rate outcome, the results are statistically significant and positively signed in almost all years in column (1), but when the comparison group is restricted to only schools with stable credit recovery enrollment, the results are no longer statistically significant (although the coefficients are larger than the coefficients in Table 15). This result indicates that credit recovery implementation has no effect on the chronic absenteeism rate once the comparison group includes only schools with stable levels of credit recovery enrollment. Regardless of the comparison group, the year trend and total effect by 2017 are both statistically insignificant.

The results in Table 17 for the EOC proficiency rate are very similar to the results in Table 13 for the high school graduation rate outcome. In both 2015 and 2017, the coefficients are statistically significant and negative. This result indicates that schools that implemented credit recovery after 2013 had lower EOC proficiency rates in 2015 and 2017. The coefficient for 2017 credit recovery implementation (post-2013 credit recovery implementation) in column (2) is nearly statistically significant (p=0.06). In all cases, the coefficients indicate a lower EOC proficiency rate by about a fifth to a quarter of a standard deviation, or approximately a five to six percentage point decrease in the proficiency rate. When the year trend for the credit recovery schools and the treatment effects by year are combined for the total effect by 2017, there is no statistically significant effect of credit recovery implementation for schools that implemented credit recovery in 2014 on EOC proficiency rates. Considering the statistically significant and positive year trend for treatment schools, and the negative and statistically significant coefficients for treatment schools in 2015 and 2017, schools implementing credit recovery experience a dip in their EOC proficiency rate either during the year of or one year after implementation, but this negative effect attenuates over time.

The results for the course failure rate outcome are listed in Table 18. These results are not to be interpreted as causal because of the lack of enough prior years of data on outcome to properly account for the trends over time. The coefficients from the treatment indicators exhibit no statistical significance. The size of the coefficients increases with each successive year, but the imprecision of the estimates also increases, such that the coefficients remain statistically insignificant. The year trend is also not statistically significant and is negatively signed.

Validity Checks

The results in Tables 13, 15, 16, and 17 only represent the causal effect of late implementation of credit recovery on the outcomes if certain assumptions of the CITS model are met. The strongest assumption is the parallel assumption, where it is assumed in the absence of treatment that the change in the outcomes of the treatment and comparison schools would have been parallel. I test for the plausibility of the parallel assumption in Figure 10 by exploring the pre-treatment trends in the outcomes of the treatment schools and comparison schools. To reflect the treatment and comparison groups in the tables, three separate trend lines are shown. The solid trend line represents the treatment group: schools that implemented credit recovery in 2014, 2015, 2016, or 2017. The dashed lines represent the comparison groups, shown in the legend as corresponding to the columns of Tables 13-18. To investigate the plausibility of the parallel assumption, the focus is comparing the solid line and the dashed lines prior to year zero (there is no pre-treatment comparison available for the course failure rate and passing rate of previously failed courses). As shown in Figure 10, the trends in the outcomes and pretreatment match relatively well between the treatment and comparison schools, since these lines do not cross and are relatively well-matched in slope.

The next validity check is the Granger test, which was used to determine whether there are treatment effects detectable prior to treatment occurring. The results of the Granger test are listed in Table 19. The results indicate that there was no detectable treatment effect prior to credit recovery implementation, regardless of the comparison group, on all coefficients except for two (passing rate of previously failed courses one year prior to treatment in Panel A, and chronic absenteeism rate one year prior to treatment on Panel B). As only two coefficients are significant out of 16, the results still indicate that these data pass the Granger test due to the possibility of multiple comparisons leading to those significant results.

The third test assesses the extent to which the comparison schools are a strong counterfactual for the treatment schools. Table 20 shows the mean values on various covariates for treatment schools as well as the two comparison groups. This table includes the standardized differences between the treatment and comparison schools. Standardized differences are a preferred method for assessing covariate balance because the traditional *t* test is susceptible to issues of power, while standardized differences are not affected by sample size. Standardized differences are considered acceptably small when they are less than 0.25. Treatment and comparison schools are balanced based on the percentage of students who are black, Hispanic, economically disadvantaged, limited English proficient (LEP), and receive special education (SPED) services. Schools are not balanced based on enrollment, with the treatment schools having much lower enrollment regardless of the choice of comparison group. Treatment schools are also less likely to be rural and have higher enrollments of gifted students. When compared to the second choice of comparison schools (schools with stable levels of credit recovery), treatment schools have higher per-pupil expenditures (School PPE). These results question the validity of these comparison groups as strong counterfactuals for the treatment group.

Dosage Analysis

In the main specification, treatment is defined as enrolling at least one student in credit recovery. However, treatment effects might only appear once schools have reached a certain threshold level of credit recovery enrollment. In Table 21 and Figures 11-16, I explore the association between the dosage of credit recovery at the school-level and changes in the outcomes. While these results were assessed using three dosage measures, I am only showing the results for two of the dosage measures, as the percentage of EOC courses that are credit recovery had very similar results to the percentage of all students enrolled in credit recovery.

These estimates are associations (not causal), and can be interpreted as the association between within-school changes in credit recovery dosage and the outcomes (taking into account the year and select time-varying school characteristics). First, the resulting coefficients on the variables indicating both the percentage of enrollment in credit recovery and the percentage of students who fail courses and are enrolled in credit recovery are shown in Table 21. The results are significant only for models with the EOC proficiency rate, course failure rate, and passing rate of previously failed courses as the dependent variables. The coefficients are difficult to interpret due to the inclusion of the squared term of enrollment. To further explore these results, these same results are presented as predicted levels on the six outcome variables across the range of the credit recovery enrollment variables in Figures 11-16. The results are calculated using Stata's *margins* post-estimation command. The blue line represents a null effect size (i.e., zero). The grey area represents the 95 percent confidence interval around each effect size. In order for an effect size to be statistically significant, the grey area should not cross over the blue null effect line. The black line represents the predicted level of the outcomes based on the results in Table 21. Each figure includes two graphs. The first graph uses the dosage measure of the percentage of all students in the school who enroll in credit recovery, which ranges in these data from zero to 65 percent. The second graph shows the percentage of students who failed courses who enroll in credit recovery, which ranges from zero to 100 percent.

Figure 11 shows the results for the high school graduation rate dependent variable; Figure 12 shows the results for the dropout rate dependent variable; and Figure 13 shows the results for the chronic absenteeism dependent variable. As indicated in Table 21, the results from these models are not statistically significant. While the CITS results show that credit recovery implementation is associated with lower graduation rates using both comparison groups, I do not find evidence that the high school graduation rate is sensitive to the dosage of credit recovery. Part of the reason why one might not expect the results from the CITS analysis to match with the dosage analysis is that both treatment and comparison schools have ranges of credit recovery enrollment across these distributions. While the treatment effect estimates for the CITS analysis is based only on within-school changes in the outcomes for treatment schools, the dosage estimates include within-school changes in credit recovery enrollment and corresponding within-school changes in the outcomes for both treatment and comparison schools (see Figure 9).

When the outcome is the EOC proficiency rate, the results in Figure 14 indicate that credit recovery dosage at the upper tail of enrollment for the percentage of all students who are in credit recovery is associated with lower EOC proficiency rates. While the results initially appear to be positive with higher credit recovery enrollments associated with higher EOC proficiency rates (insignificant, but positive in sign), the results turn negative at about 43 percent enrollment, and become statistically significant and negative soon after. This is reflected in Table 21, where the coefficients on percentage enrollment and percentage enrollment squared are statistically significant. Percentage of enrollment in credit recovery is positively signed, but percentage of enrollment squared is negatively signed, leading to the initially positive-looking result, but eventually negative association between credit recovery enrollment and EOC proficiency rates. These results correspond more directly to the results from the CITS analysis in that they both indicate negative associations between credit recovery and test score proficiency.

The course failure rate outcome is shown in Figure 15. Using the enrollment measure of the percentage of all students in credit recovery, I find that credit recovery enrollment is associated with increasingly higher course failure rates after an approximate ten percent dosage level. At the upper tail of the distribution, the course failure rate is predicted to be about one standard deviation above the mean. This is also shown in Table 21, where the coefficient on credit recovery enrollment is significant and positive (the coefficient on the squared term is positive, but not statistically significant). This result indicates that the course failure rate is predicted to increase monotonically, with increases in credit recovery enrollment.

Figure 16 shows the results for the passing rate of previously failed courses outcome. For both dosage measures, as shown in Table 21, there is an overall positive relationship between credit recovery dosage and the passing rate of previously failed courses. Using the measure of the percentage of all students enrolled in credit recovery, the relationship is quadratic, since the coefficient on the percentage of all students enrolled in credit recovery squared is significant and negative, while the non-squared term is significant and positive. As shown in Figure 16, the relationship between the percentage of all students enrolled in credit recovery and the passing rate of previously failed courses is initially negative until about ten percent enrollment. The relationship is increasingly positive until the turning point at 41 percent,[15] when the relationship attenuates (the association would eventually become negative, but the actual range of the percentage of all students enrolled in credit recovery ends at 65 percent). The only model where the percentage of students who fail courses and enroll in credit recovery is statistically significant is when predicting the passing rate of previously failed courses. The coefficient on this variable and the squared version are both statistically significant and positive, indicating an exponential relationship between the percentage of students who failed courses in credit recovery and the passing rate of previously failed courses. This strong positive relationship is shown on Figure 16.

Conclusion

As schools increase enrollments in credit recovery, high-quality evaluations of the impact of credit recovery on school-level outcomes are an important step in making evidence-based decisions about whether online learning is an effective intervention for improving the outcomes of at-risk students. This study represents an attempt to do so, albeit with some caveats to establish before causal claims can be made. An ideal study of credit recovery would include an earlier time period to truly capture when credit recovery was implemented in schools. This study

[15] The formula for the turning point is $-b/2a$, where b is the coefficient on the non-squared term, and a is the coefficient on the squared term. With the values from Table 21, this equation would be $-1.26/(2\times-0.154)=4.1$. Since the enrollment measures in Table 21 were the percentages in 10s, the actual turning point percent is 4.1×10, or 41 percent.

is essentially investigating the effect of *late adoption* of credit recovery due to the lack of data from an earlier time period. Late adoption of credit recovery could differ from earlier implementation of credit recovery in important ways. For instance, online course providers could have significantly improved in response to feedback from schools. Also, early implementers of credit recovery could have shared best practices with late adopters, such that these schools would start off with more knowledge of effective implementation than that with which the early implementers began.

Given that the validity checks on the comparative interrupted time series analysis appear to hold, the evidence indicates that late adoption of credit recovery leads to lower test scores and graduation rates. The challenge to the causality of these estimates is mainly the nature of the comparison group—it is formed from schools that had previously implemented credit recovery and are not expected to change. The use of school fixed effects estimates the effects using within school variability over time as opposed to differences between schools when calculating the effect sizes. The school fixed effects are an important aspect of the identification strategy, since it eliminates between-school variation, such that the schools, in essence, serve as their own comparison group where the effect sizes represented within a school changes over time.

However, it must be emphasized that schools that initiated credit recovery in this time period are different from the comparison schools in several measureable ways. For instance, approximately half of the schools that implemented credit recovery in this time period are "Early College" or "Middle College" schools that have partnerships with local community colleges and universities to offer college credit and/or the opportunity to earn an associate's degree. These schools might have systematically implemented and used credit recovery in ways that are different from traditional high schools. I find some evidence in models where the treatment effect is allowed to vary between Early College/Middle College schools and other treatment schools, and the effects are primarily being driven by the implementation of credit recovery in Early College/Middle College schools. For example, when the results are separated between Early College/Middle College schools and other treatment schools for the end-of-course proficiency rate outcome, the results are statistically significant and negative for the 2015 and 2017 coefficients for Early College/Middle College schools, but are not statistically significant for other treatment schools.

Descriptively, higher credit recovery enrollment is associated with lower EOC proficiency rates and higher course failure rates. Despite the findings that implementing credit recovery leads to lower high school graduation rates, dosage is not associated with higher or lower high school graduation rates. This indicates that the inclusion of credit recovery alone leads to lower high school graduation rates, regardless of the dosage. The results on the EOC proficiency rates and course failure rates are consistent across the causal and dosage analysis; even though the course failure rate results were not significant in the CITS model, the coefficients were large and positively signed. When examining the raw data graphically, we see that treatment schools greatly increase credit recovery enrollments over time, representing a significant portion of schools with high credit recovery enrollments (also see Figure 9). While treatment schools have lower graduation rates than comparison schools, treatment schools with the highest increases in credit recovery enrollments do have increasingly higher graduation rates, which could lead to the different findings across the CITS and dosage analysis. When the same means are compared for the EOC proficiency rates, treatment schools with larger changes in credit recovery enrollment have lower proficiency rates. This might be part of the reason why the results are consistent for the EOC proficiency rates, but not the high school graduation rates.

Schools with significant credit recovery enrollment rates have higher passing rates of previously failed courses, and schools with lower credit recovery enrollment rates tended to be associated with slightly lower passing rates. Descriptively, credit recovery appears to meet its most proximal goal of increasing credit accumulation of students who are failing courses in high school. These estimates are descriptive, since increasing credit recovery enrollment and increases/decreases in these outcomes could be related to an underlying omitted variable unaccounted for by the school and year fixed effects. For instance, schools with a growing teacher shortage might be more likely to place students in credit recovery where they will not need an instructor to complete the course, and these same schools could have lower test scores due to lowered human capital capacity. I did attempt to empirically test the hypothesis that teacher shortages could account for these results, finding no evidence that teacher shortages are related to credit recovery enrollment.

The evidence presented in this paper presents a call for caution as schools and districts make decisions about credit recovery programs. While credit recovery might theoretically be an effective tool to increase graduation rates by increasing course credits, the evidence presented here does not fully support this hypothesis.

APPENDIX

Table 12: Credit Recovery Schools by Year

	No Credit Recovery	Post Credit Recovery	Total
2013	104	471	575
2014	60	515	575
2015	42	533	575
2016	36	539	575
2017	31	544	575
Total School by Year Observations	273	2602	2875

Once a school is observed as having credit recovery, they are counted as being post-credit recovery for the remainder of the time period. Sample only includes schools with data for all years between 2013 and 2017.

Table 13: Dependent Variable is High School Graduation Rate, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	-0.04***	-0.04***
	(0.01)	(0.01)
2014	0.07*	0.06*
	(0.03)	(0.03)
2015	0.10**	0.09**
	(0.04)	(0.04)
2016	0.11*	0.12**
	(0.04)	(0.04)
2017	0.42***	0.37***
	(0.05)	(0.05)
Year X Ever CR (no 2013)	0.02	0.02
	(0.01)	(0.02)
CR in 14, no 13 CR Schools	-0.19	-0.17
	(0.12)	(0.12)
CR in 15, no 13 CR Schools	-0.25**	-0.21*
	(0.09)	(0.09)
CR in 16, no 13 CR Schools	-0.15	-0.12
	(0.12)	(0.11)
CR in 17, no 13 CR Schools	-0.46***	-0.35***
	(0.10)	(0.10)
Total effect by 2017	-0.39***	-0.28***
	(0.08)	(0.08)
Observations	5511	3207
R^2	0.04	0.04

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Dependent Variable is Passing Rate of Previously Failed Courses, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	0.01	0.01
	(0.02)	(0.03)
2014	0.04	-0.04
	(0.06)	(0.05)
2015	0.04	0.02
	(0.04)	(0.05)
2016	0.07	0.02
	(0.04)	(0.05)
Year X Ever CR (no 2013)	-0.12 (0.13)	-0.08 (0.14)
CR in 14, no 13 CR Schools	0.27 (0.18)	0.30 (0.19)
CR in 15, no 13 CR Schools	0.36 (0.29)	0.36 (0.30)
CR in 16, no 13 CR Schools	0.31 (0.39)	0.29 (0.40)
CR in 17, no 13 CR Schools	0.92 (0.53)	0.85 (0.56)
Total association by 2017	0.42 (0.39)	0.54 (0.40)
Observations	2673	1524
R^2	0.01	0.04

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Dependent Variable is Dropout Rate, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	-0.06***	-0.07***
	(0.01)	(0.01)
2014	-0.41***	-0.21***
	(0.04)	(0.03)
2015	-0.35***	-0.15***
	(0.05)	(0.02)
2016	-0.28***	-0.07**
	(0.05)	(0.03)
Year X Ever CR (no 2013)	0.01	0.01
	(0.02)	(0.02)
CR in 14, no 13 CR Schools	0.22**	0.05
	(0.08)	(0.08)
CR in 15, no 13 CR Schools	0.19*	0.01
	(0.09)	(0.07)
CR in 16, no 13 CR Schools	0.22*	0.00
	(0.09)	(0.08)
Total effect by 2016	0.24***	0.03
	(0.08)	(0.07)
Observations	5967	3618
R^2	0.17	0.26

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Dependent Variable is Chronic Absenteeism Rate, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	-0.01	-0.01
	(0.01)	(0.01)
2014	-0.53***	-0.32***
	(0.04)	(0.04)
2015	-0.54***	-0.35***
	(0.04)	(0.05)
2016	-0.48***	-0.34***
	(0.05)	(0.05)
2017	-0.48***	-0.29***
	(0.06)	(0.06)
Year X Ever CR (no 2013)	-0.03	-0.03
	(0.02)	(0.02)
CR in 14, no 13 CR Schools	0.28*	0.11
	(0.14)	(0.14)
CR in 15, no 13 CR Schools	0.29*	0.15
	(0.13)	(0.13)
CR in 16, no 13 CR Schools	0.22	0.13
	(0.13)	(0.13)
CR in 17, no 13 CR Schools	0.30*	0.16
	(0.15)	(0.15)
Total effect by 2017	0.17	0.04
	(0.10)	(0.10)
Observations	6547	3989
R^2	0.16	0.16

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Dependent Variable is EOC Proficiency Rate, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	0.02***	0.03***
	(0.01)	(0.01)
2014	0.19***	0.17***
	(0.02)	(0.03)
2015	0.17***	0.16***
	(0.02)	(0.03)
2016	0.10***	0.06
	(0.03)	(0.03)
2017	0.08*	0.03
	(0.03)	(0.04)
Year X Ever CR (no 2013)	0.07***	0.06***
	(0.02)	(0.02)
CR in 14, no 13 CR Schools	-0.07	-0.06
	(0.09)	(0.09)
CR in 15, no 13 CR Schools	-0.23*	-0.22*
	(0.09)	(0.09)
CR in 16, no 13 CR Schools	-0.10	-0.08
	(0.11)	(0.11)
CR in 17, no 13 CR Schools	-0.26*	-0.22
	(0.11)	(0.11)
Total effect by 2017	0.01	0.03
	(0.07)	(0.07)
Observations	6006	3492
R^2	0.28	0.35

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Dependent Variable is Course Failure Rate, Standardized

	(1) Restricted to Schools with CR	(2) Restricted to Schools Introducing CR or with Stable CR
Year Centered	-0.01	-0.04*
	(0.01)	(0.02)
2014	0.02	-0.08*
	(0.03)	(0.03)
2015	0.02	-0.05
	(0.03)	(0.03)
2016	0.02	0.01
	(0.02)	(0.02)
Year X Ever CR (no 2013)	-0.09 (0.07)	-0.03 (0.07)
CR in 14, no 13 CR Schools	0.07 (0.07)	0.12 (0.07)
CR in 15, no 13 CR Schools	0.15 (0.09)	0.14 (0.09)
CR in 16, no 13 CR Schools	0.26 (0.14)	0.17 (0.13)
CR in 17, no 13 CR Schools	0.37 (0.20)	0.22 (0.20)
Total association by 2017	0.01 (0.11)	0.11 (0.10)
Observations	2719	1637
R^2	0.03	0.07

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Granger Test

	(1) HS Graduation Rate	(2) Dropout Rate	(3) EOC Performance Composite	(4) Chronic Absenteeism Rate	(5) Course Failure Rate	(6) Passing Rate
Panel A: Restricted to Schools with CR						
Two Years Prior to Treatment	-0.13	0.05	-0.04	0.04	0.02	-0.37
	(0.08)	(0.10)	(0.08)	(0.12)	(0.31)	(0.37)
One Year Prior to Treatment	-0.05	-0.08	0.18	-0.27	-0.18	-0.65*
	(0.09)	(0.11)	(0.13)	(0.14)	(0.29)	(0.28)
Observations	5511	5967	6006	6547	2719	2673
Panel B: Restricted to Schools Introducing CR or with Stable CR						
Two Years Prior to Treatment	-0.11	0.02	-0.05	0.02	-0.02	-0.35
	(0.08)	(0.10)	(0.08)	(0.12)	(0.30)	(0.39)
One Year Prior to Treatment	-0.02	-0.15	0.17	-0.32*	-0.21	-0.59
	(0.09)	(0.11)	(0.13)	(0.14)	(0.29)	(0.32)
Observations	3207	3618	3492	3989	1637	1524

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Balance

	Treatment	Comparison Schools with CR		Comparison Schools, Stable CR	
	Mean (SD)	Mean (SD)	Std. Diff	Mean (SD)	Std. Diff
Enrollment	2.56	8.51	**1.30**	9.08	**1.63**
(in 100s)	2.34	6.05		5.14	
Percent Black	28.99	28.88	0.00	26.61	0.10
	26.68	22.66		20.71	
Percent Hispanic	10.88	10.98	0.01	10.95	0.01
	8.89	8.11		7.62	
Percent Economically	49.20	53.36	0.16	48.19	0.04
Disadvantaged	28.09	25.01		20.15	
City	0.35	0.27	0.17	0.24	0.24
	0.48	0.45		0.43	
Rural	0.42	0.57	**0.30**	0.59	**0.35**
	0.50	0.50		0.49	
Suburb	0.10	0.08	0.08	0.09	0.04
	0.30	0.27		0.28	
Town	0.13	0.08	0.16	0.07	0.17
	0.34	0.27		0.26	
School PPE	12320	10666	0.18	8837	**0.42**
	11127	6935		3484	
Percent LEP	3.25	3.14	0.01	3.03	0.03
	11.92	3.24		2.96	
Percent SPED	29.42	29.05	0.03	28.66	0.05
	17.37	10.81		9.65	
Percent Gifted	19.58	14.71	**0.39**	16.53	**0.26**
	14.63	9.57		8.21	

Standard deviations in parentheses. Standardized differences are calculated as $\frac{|\mu_T - \mu_C|}{\sqrt{(\sigma_T^2 + \sigma_C^2)/2}}$. Standardized differences are assessed with the Treatment group in all cases. Standardized differences above 0.25 are bolded.

Table 21: Results from Dosage Models Predicting the Outcomes Based on Percentage of Enrollment in Credit Recovery Using School Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	HS Graduation Rate		Dropout Rate		EOC Proficiency Rate		Chronic Absenteeism Rate		Percent of Core Course Failures		Passing Percent of Failed Courses	
Percent of all students enrolled in CR (in 10s)	0.041 (0.064)		0.046 (0.077)		0.056* (0.026)		0.107 (0.060)		0.139* (0.059)		1.260*** (0.301)	
Percent (in 10s) squared	0.009 (0.014)		-0.011 (0.019)		-0.013** (0.004)		-0.025 (0.016)		0.007 (0.013)		-0.154*** (0.036)	
Percent of failed students enrolled in CR (in 10s)		0.012 (0.013)		-0.006 (0.014)		0.008 (0.008)		-0.003 (0.013)		0.013 (0.010)		0.320*** (0.050)
Percent (in 10s) squared		-0.0002 (0.0003)		0.0001 (0.0002)		0.0000003 (0.0002)		0.0004 (0.0003)		-0.0004 (0.0002)		0.004** (0.001)
Observations	2590	2576	2235	2186	2720	2705	2807	2744	2778	2741	2670	2670
R^2	0.06	0.06	0.01	0.01	0.06	0.06	0.03	0.03	0.06	0.03	0.13	0.51

Standard errors in parentheses, standard errors clustered at the school level. Covariates not included for brevity.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9: Trends in Credit Recovery Enrollment Over Time

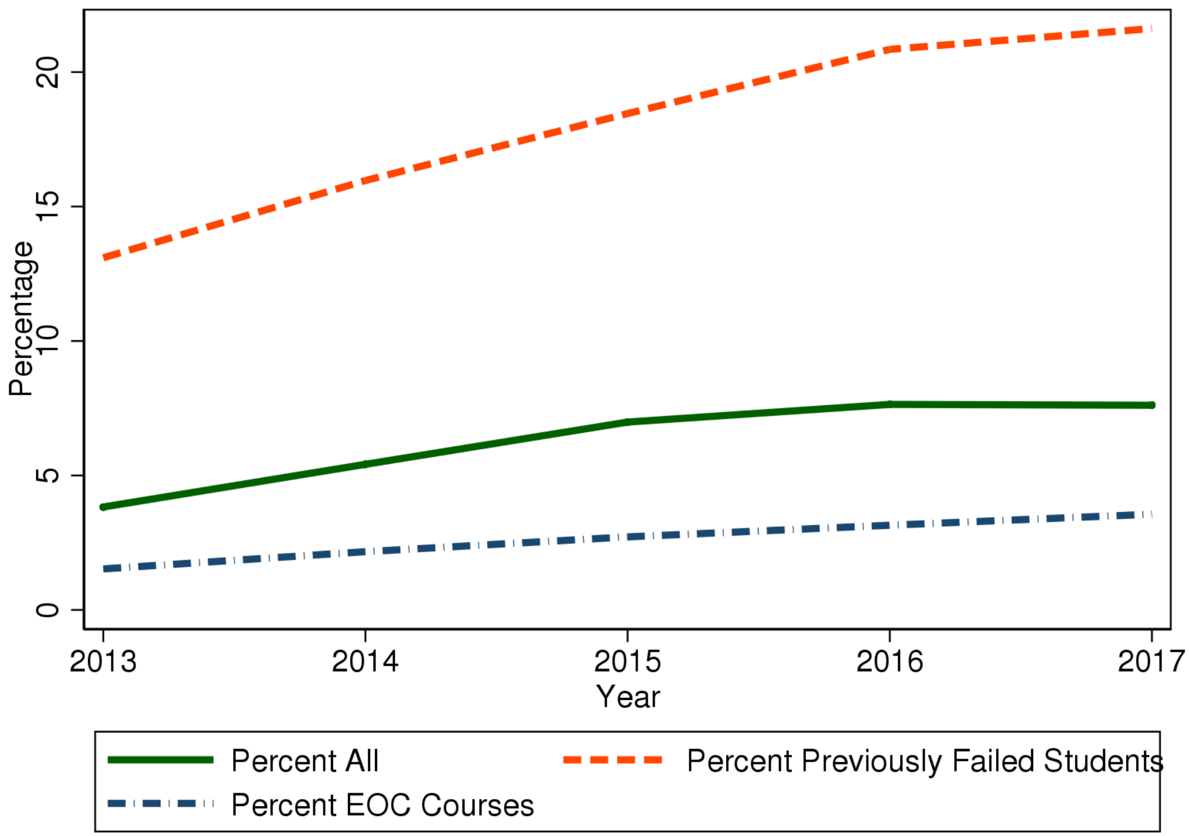


Figure 10: Pretreatment Trends

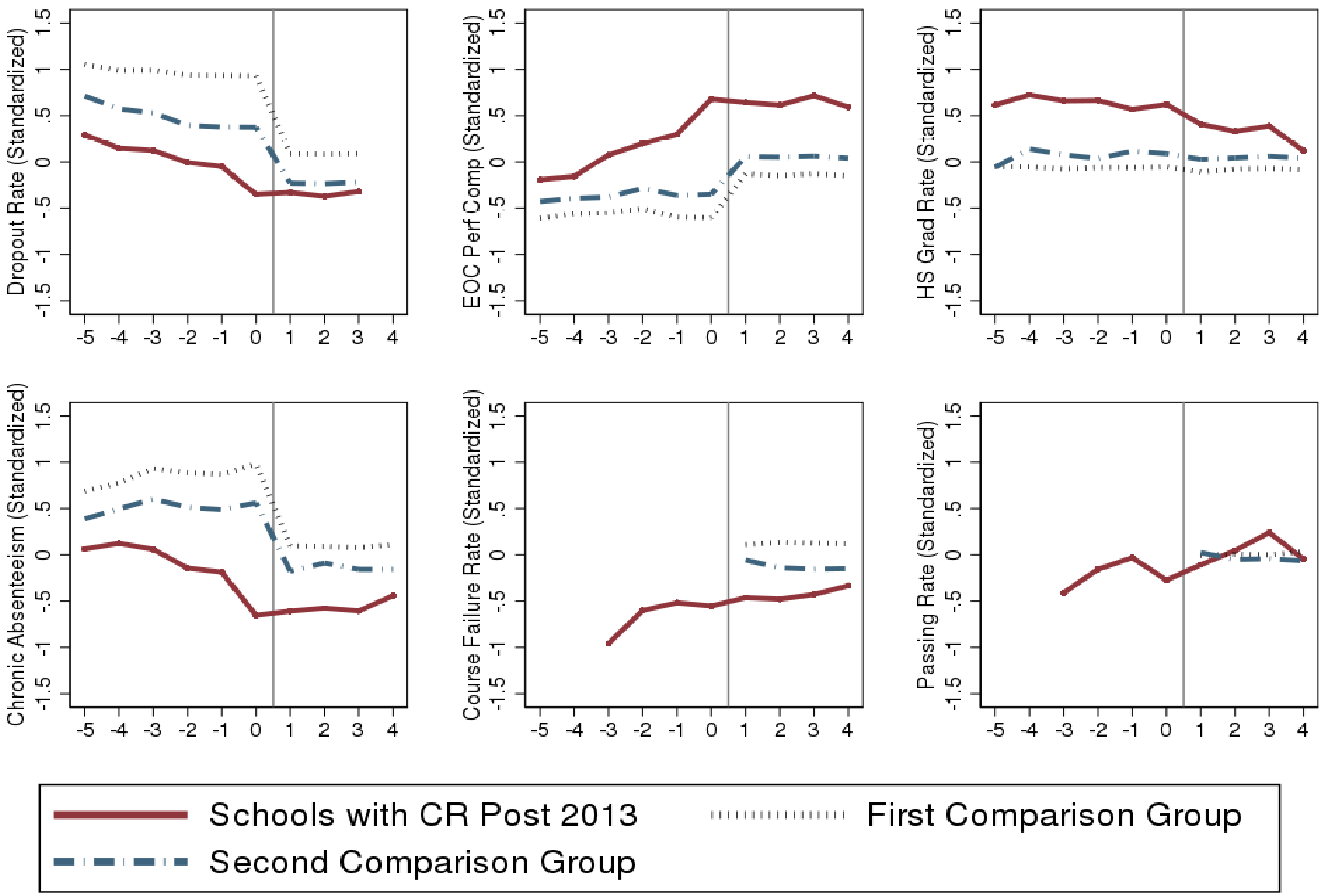


Figure 11: Predicted Standardized High School Graduation Rate Based on Credit Recovery Enrollment

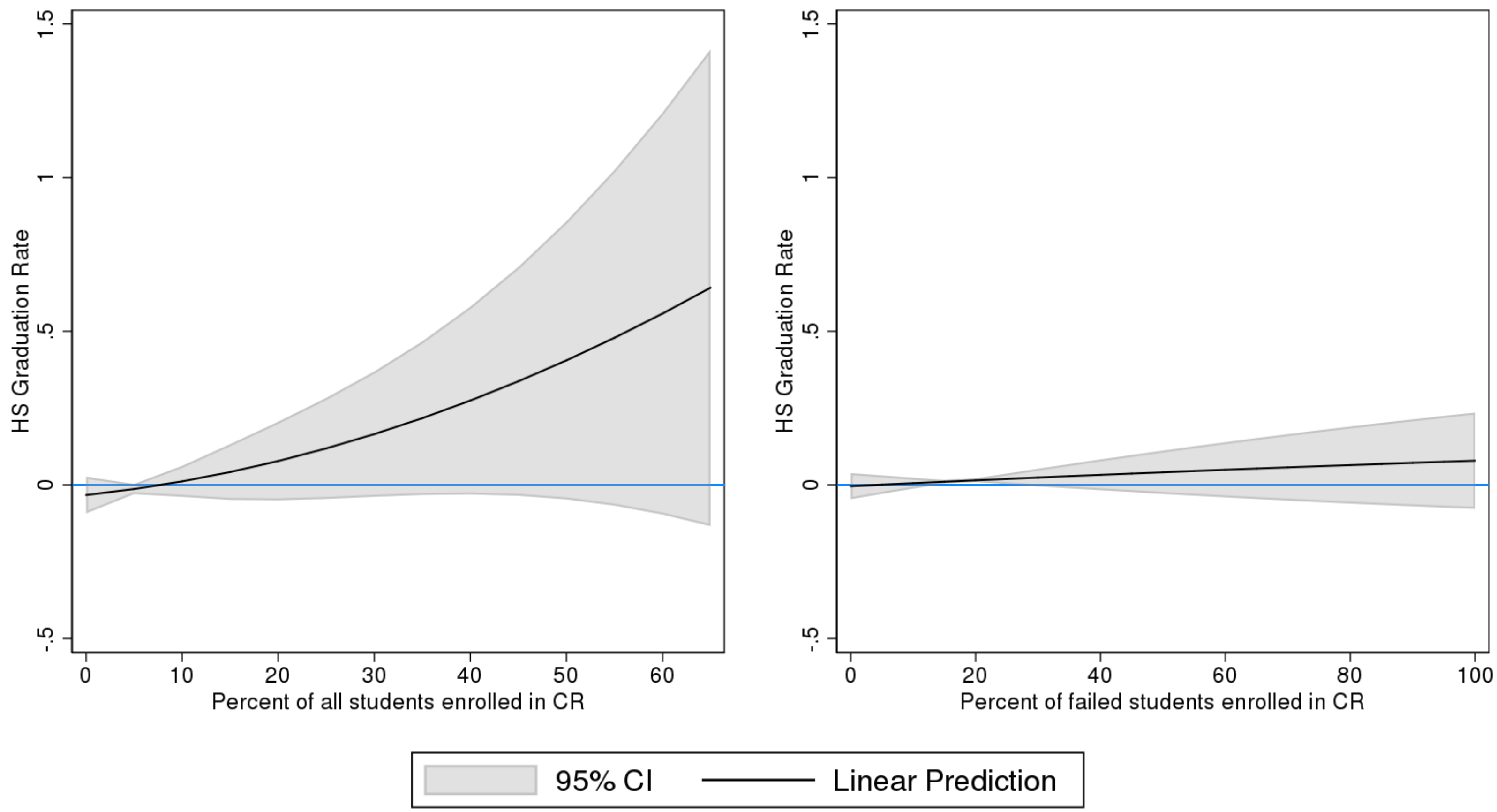


Figure 12: Predicted Standardized Dropout Rate Based on Credit Recovery Enrollment

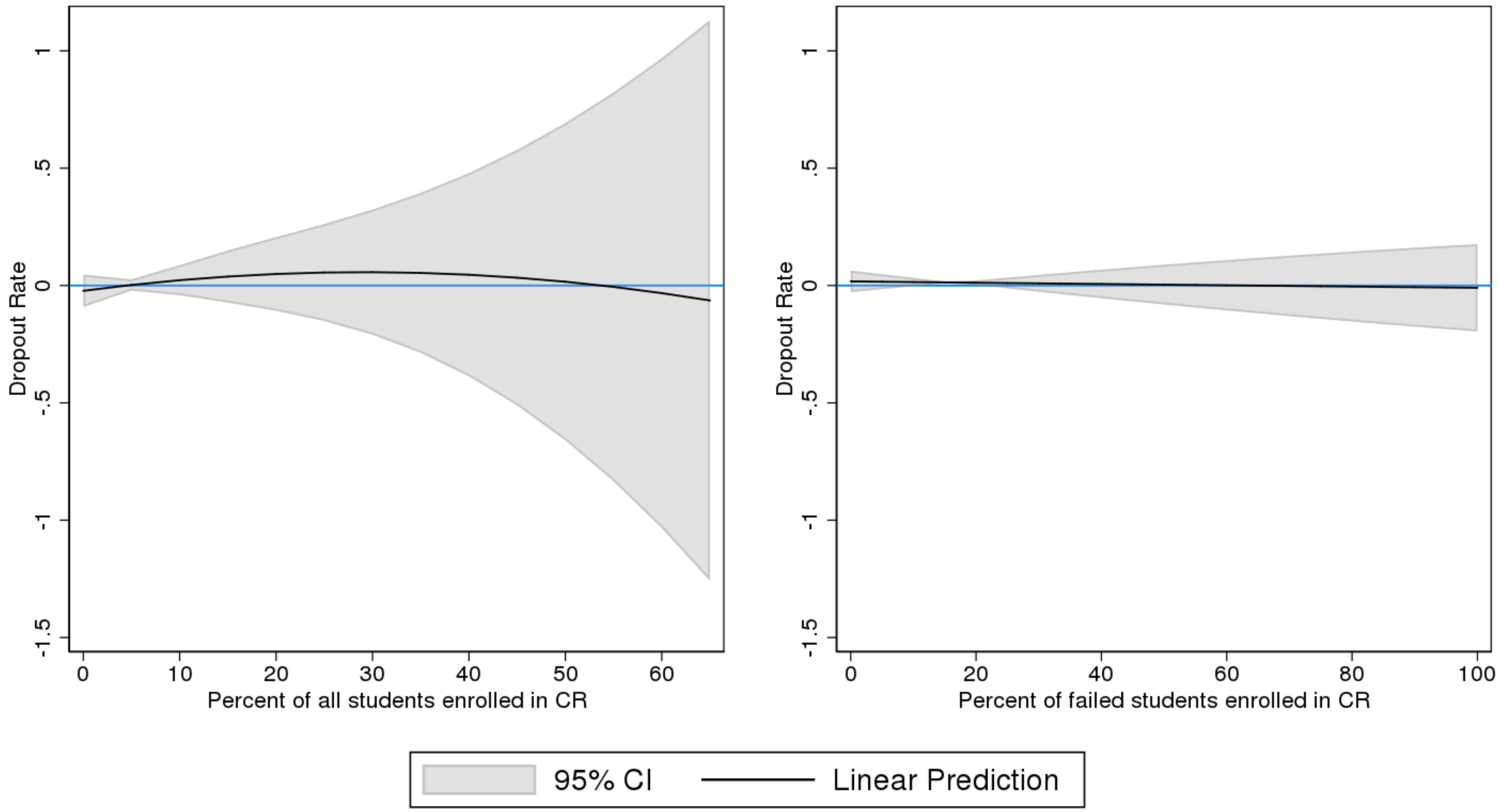


Figure 13: Predicted Standardized Chronic Absenteeism Rate Based on Credit Recovery Enrollment

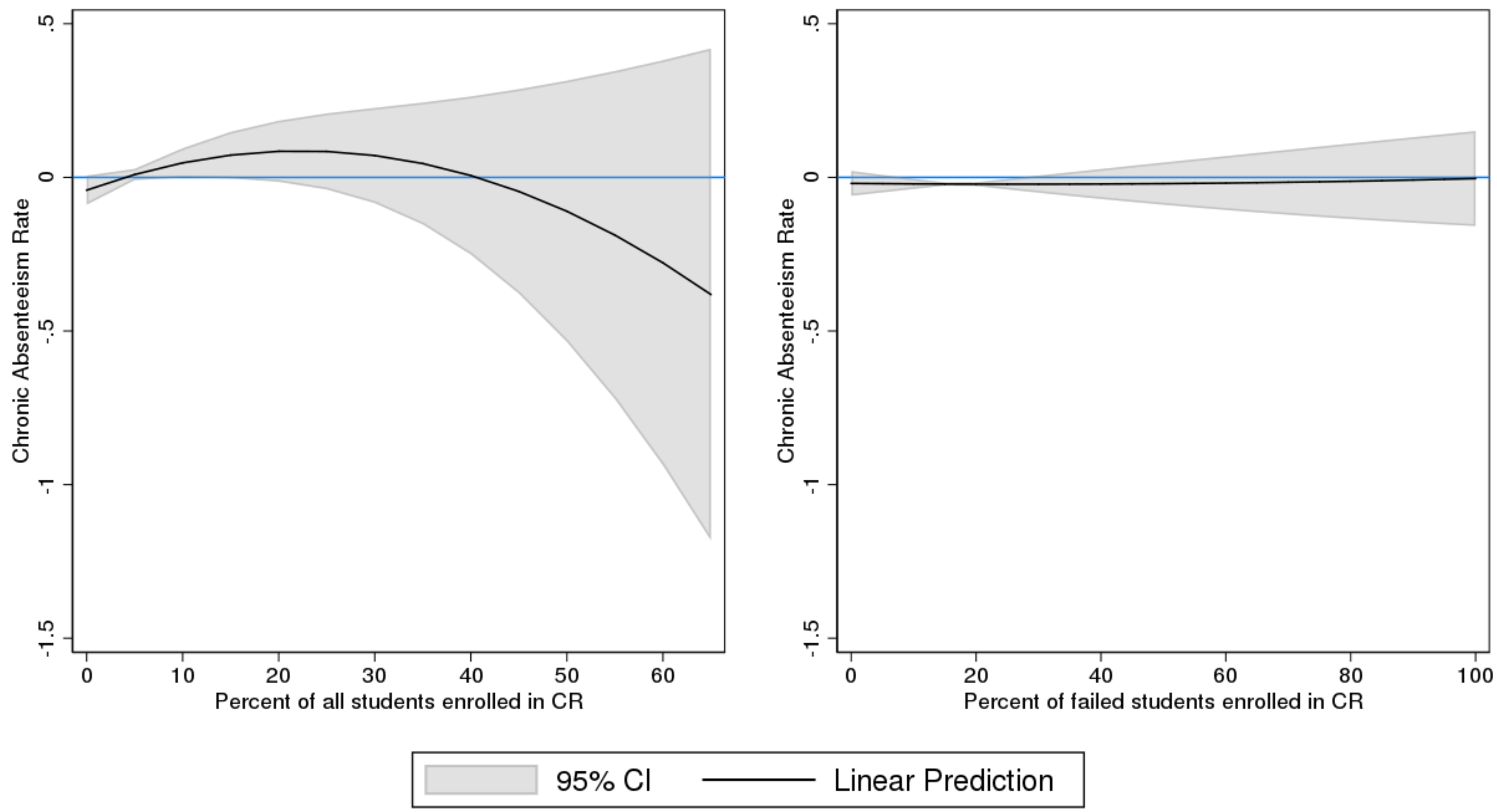


Figure 14: Predicted Standardized EOC Proficiency Rate Based on Credit Recovery Enrollment

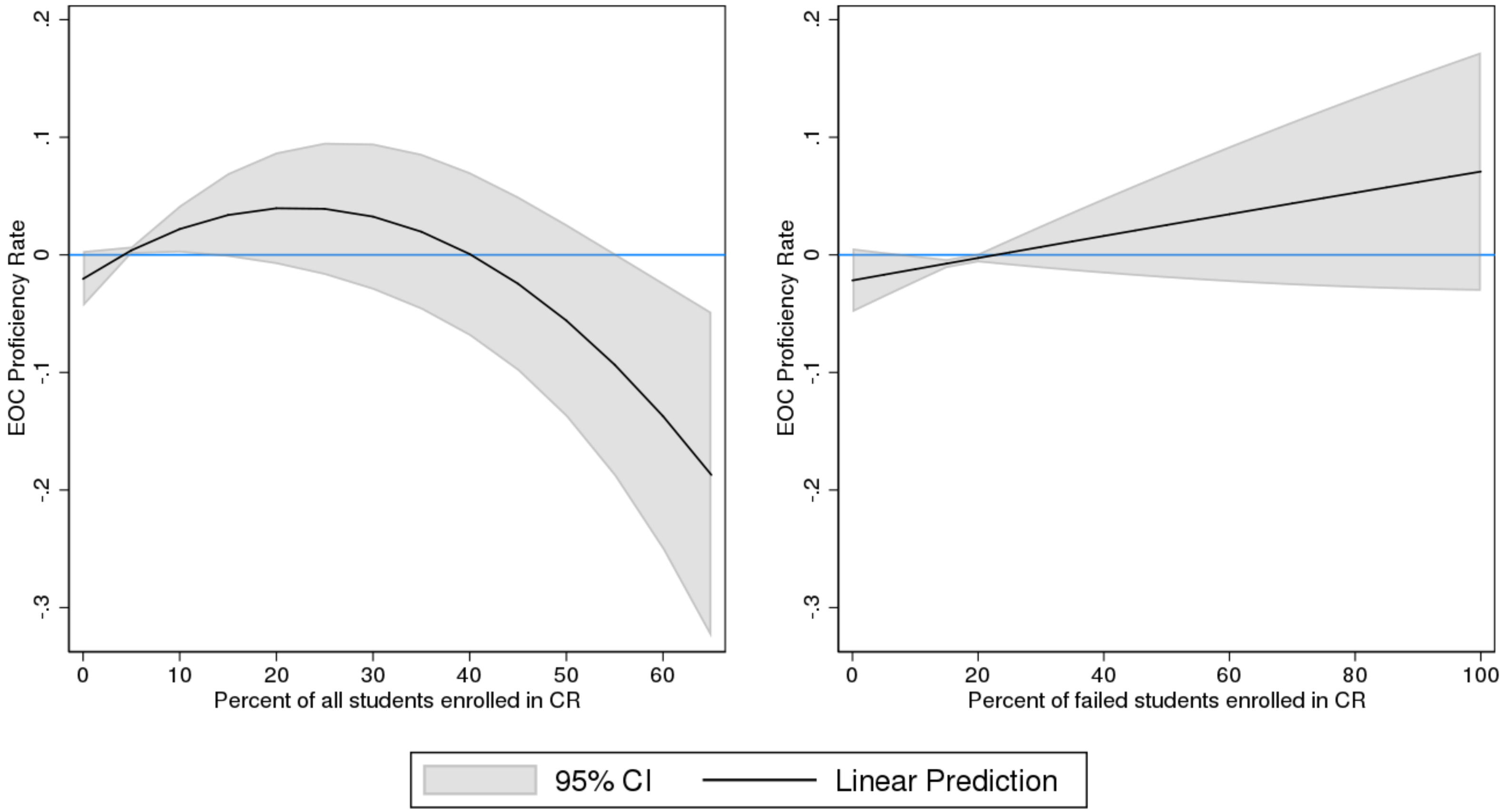


Figure 15: Predicted Standardized Core Course Failure Rate Based on Credit Recovery Enrollment

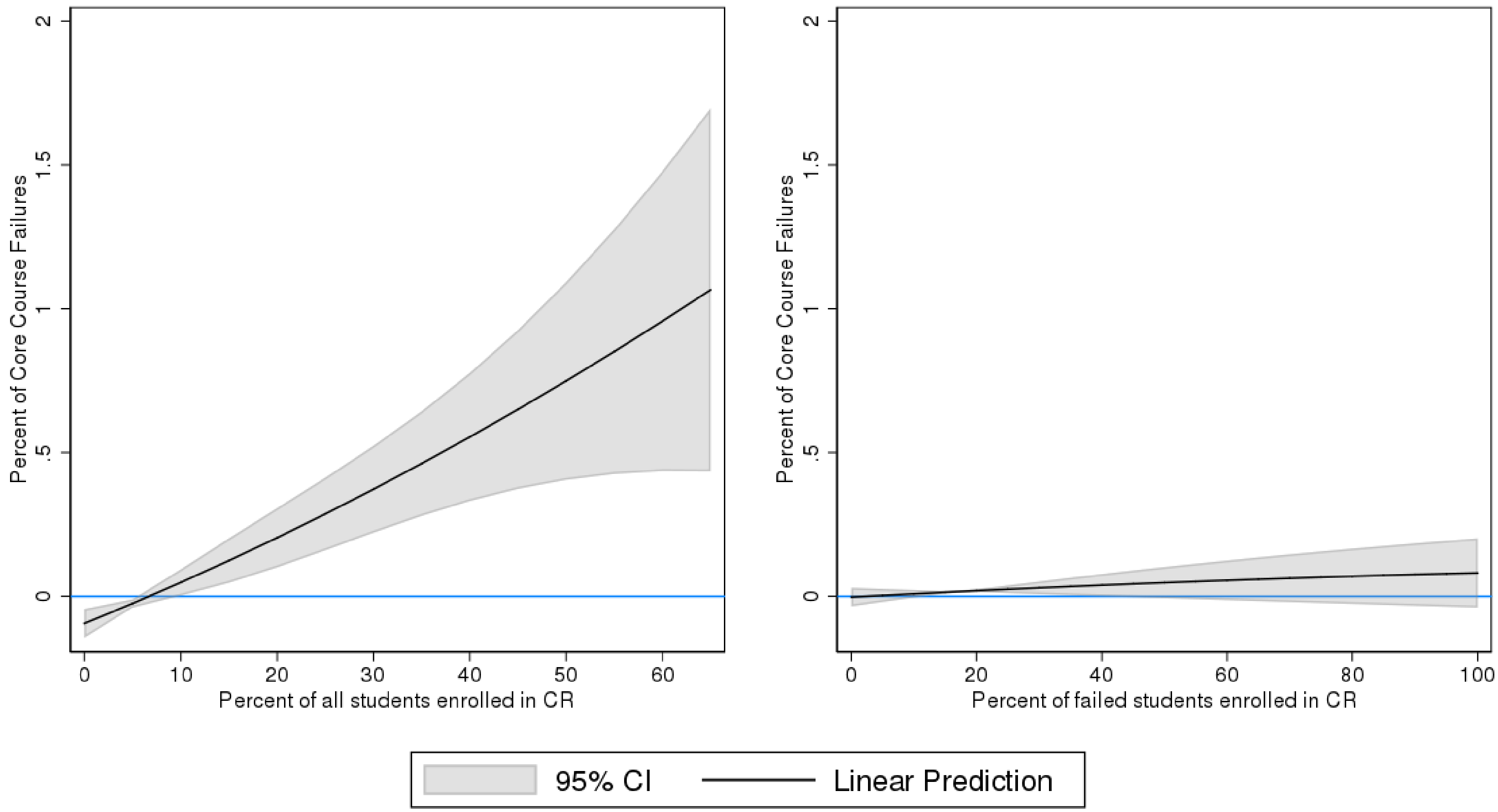


Figure 16: Predicted Standardized Passing Rate of Previously Failed Courses Based on Credit Recovery Enrollment

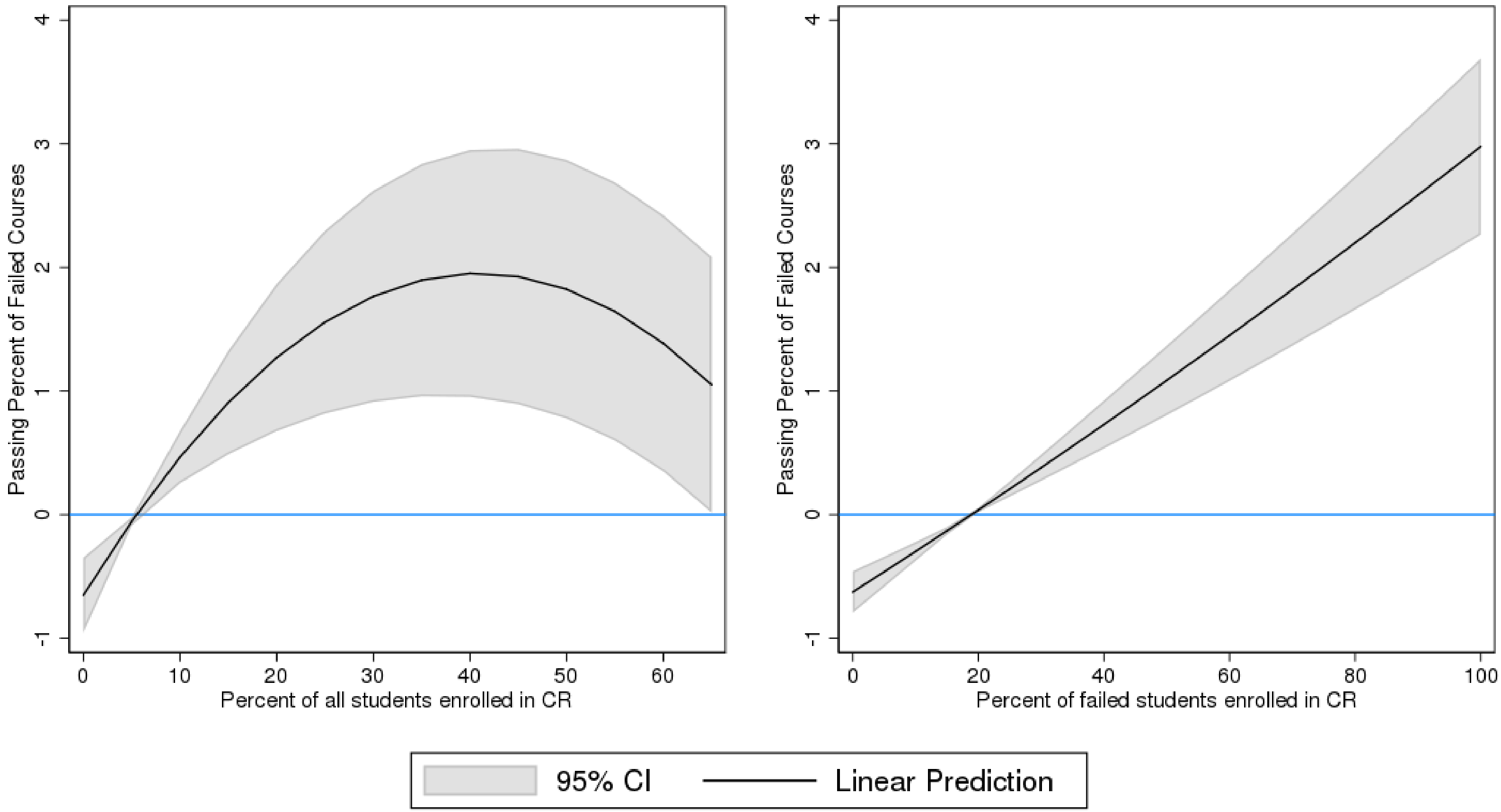
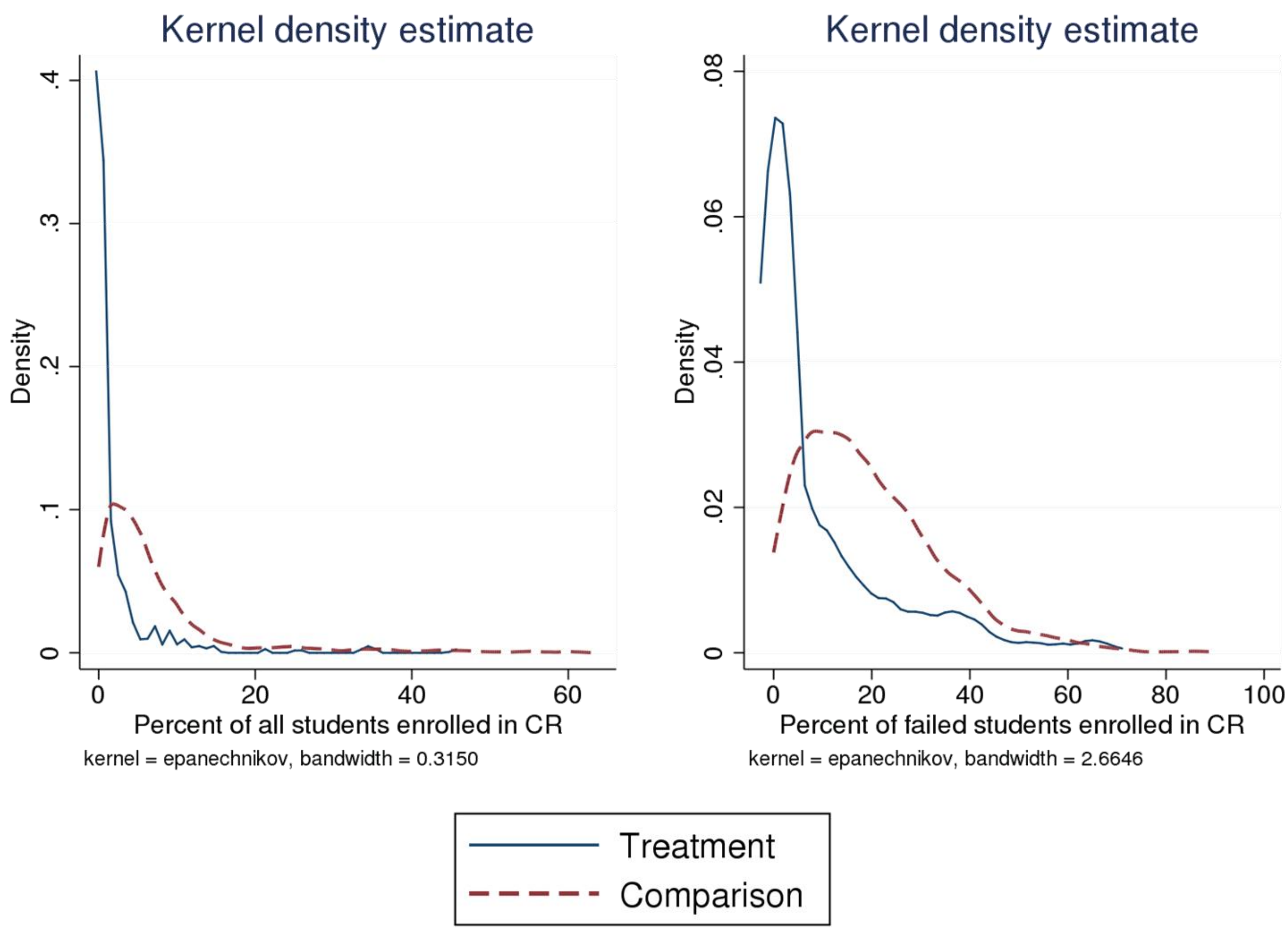


Figure 17: Kernel Density Distribution of Schools Based on Enrollment in Credit Recovery and Treatment Status from the CITS Analysis



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APPENDIX

A. Comparison of Weighted and Unweighted Linear Probability Models

Table A1: Comparison of Weighted and Unweighted Ordinary Least Squares Regression Estimates Using a Matched Sample

	(1)	(2)	(3)	(4)
	Unweighted		Weighted	
	Grad in Four	Drop Out	Grad in Four	Drop Out
Credit Recovery	1.03***	0.94***	1.04***	0.94***
	(0.00)	(0.00)	(0.00)	(0.00)
Black	1.12***	0.88***	1.12***	0.88***
	(0.01)	(0.00)	(0.01)	(0.01)
Hispanic	1.02*	0.96***	1.02*	0.95***
	(0.01)	(0.01)	(0.01)	(0.01)
Other Race	1.01	0.97***	1.01	0.96***
	(0.01)	(0.01)	(0.01)	(0.01)
Female	1.03***	0.99**	1.03***	0.99
	(0.00)	(0.00)	(0.01)	(0.00)
Gifted in 8th	0.97*	1.02	0.96**	1.03*
	(0.01)	(0.01)	(0.01)	(0.01)
SPED in 8th	0.99**	0.98***	0.99	0.98***
	(0.00)	(0.00)	(0.01)	(0.01)
Was LEP in 8th	1.07***	0.94***	1.07***	0.94***
	(0.01)	(0.01)	(0.02)	(0.01)
LEP in 8th	1.05***	0.94***	1.06***	0.94***
	(0.01)	(0.01)	(0.01)	(0.01)
Economically Disadvantaged	0.93***	1.05***	0.93***	1.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Percent Absences in 8th	0.99***	1.01***	0.98***	1.01***

	(0.00)	(0.00)	(0.00)	(0.00)
Approximate Age in 8th	0.94***	1.09***	0.94***	1.09***
	(0.00)	(0.00)	(0.00)	(0.00)
Average Test Scores in 8th	1.05***	0.97***	1.05***	0.96***
	(0.00)	(0.00)	(0.00)	(0.00)
Failed a Course in 8th	0.94***	1.04***	0.94***	1.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Remedial courses in 8th	0.92***	1.03*	0.91***	1.05*
	(0.01)	(0.02)	(0.02)	(0.02)
Accelerated courses in 8th	1.05***	0.98***	1.04***	0.98**
	(0.01)	(0.01)	(0.01)	(0.01)
GPA in 8th	1.10***	0.93***	1.10***	0.93***
	(0.00)	(0.00)	(0.01)	(0.00)
Observations	51534	51534	51534	51534

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Unweighted						Weighted					
	Drop Out			Grad Four			Drop Out			Grad Four		
Credit Recovery Student	0.95***	0.94***	0.96***	1.06***	1.06***	1.03**	0.94***	0.94***	0.96***	1.06***	1.07***	1.02*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Black	0.89***			1.11***			0.88***			1.12***		
	(0.01)			(0.01)			(0.01)			(0.01)		
Black Credit Recovery Student	0.99			1.01			0.99			1.01		
	(0.01)			(0.01)			(0.01)			(0.01)		
Hispanic		0.97***			1.04**			0.96**			1.07***	
		(0.01)			(0.01)			(0.01)			(0.02)	
Hispanic Credit Recovery Student		0.99			1.01			0.99			1.00	
		(0.01)			(0.01)			(0.01)			(0.02)	
Economically Disadvantaged			1.06***			0.92***			1.07***			0.91***
			(0.01)			(0.01)			(0.01)			(0.01)
Economically Disadvantaged Credit Recovery Student			0.97**			1.04***			0.97**			1.05***
			(0.01)			(0.01)			(0.01)			(0.01)
Observations	51534	51534	51534	28243	28243	28243	51534	51534	51534	28243	28243	28243

B. Using Percent Absences in Eighth Grade Quintile for Coarsened Exact Matching Instead of Eighth Grade Test Score

Table B1: Balance Check after Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.43	0.49	0.07	0.99
	Not CR	0.46	0.50		
Student is Hispanic	CR	0.17	0.38	0.15	1.17
	Not CR	0.12	0.32		
Student is Other Race	CR	0.08	0.27	0.05	1.09
	Not CR	0.06	0.24		
Student is Female	CR	0.37	0.48	0.09	0.98
	Not CR	0.42	0.49		
Student was Gifted (8th Grade)	CR	0.03	0.18	0.01	1.02
	Not CR	0.03	0.17		
Student was SPED (8th Grade)	CR	0.22	0.41	0.07	1.06
	Not CR	0.19	0.39		
Student was Previously LEP (8th Grade)	CR	0.05	0.22	0.10	1.26
	Not CR	0.03	0.17		
Student was LEP (8th Grade)	CR	0.09	0.28	0.10	1.17
	Not CR	0.06	0.24		
Student is Economically Disadvantaged	CR	0.80	0.40	0.00	1.00
	Not CR	0.80	0.40		
Percent Days Absent (8th Grade)	CR	6.86	6.25	0.00	1.03
	Not CR	6.84	6.05		
Approximate Age (8th Grade)	CR	14.58	0.63	0.04	1.03
	Not CR	14.55	0.61		
Average 8th Test Score (8th Grade)	CR	-0.58	0.74	0.09	1.00
	Not CR	-0.51	0.74		
Failed a Course (8th Grade)	CR	0.41	0.49	0.12	1.03
	Not CR	0.35	0.48		
Took Remedial Course (8th Grade)	CR	0.02	0.14	0.03	1.13
	Not CR	0.02	0.12		
Took Advanced Course (8th Grade)	CR	0.14	0.34	0.03	0.97
	Not CR	0.14	0.35		
GPA (8th Grade)	CR	2.27	0.72	0.16	1.00
	Not CR	2.38	0.72		

Table B2: Results from Logistic Regression with School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.18***	0.58***
	(0.02)	(0.01)
Black	1.74***	0.48***
	(0.05)	(0.01)
Hispanic	1.09	0.81***
	(0.05)	(0.04)
Other Race	1.07	0.83***
	(0.04)	(0.04)
Female	1.22***	0.92***
	(0.03)	(0.02)
Gifted in 8th	0.92	1.03
	(0.06)	(0.08)
SPED in 8th	0.96	0.87***
	(0.02)	(0.02)
Was LEP in 8th	1.34***	0.63***
	(0.08)	(0.04)
LEP in 8th	1.28***	0.70***
	(0.07)	(0.04)
Economically Disadvantaged	0.69***	1.37***
	(0.02)	(0.04)
Percent Absences in 8th	0.92***	1.08***
	(0.00)	(0.00)
Approximate Age in 8th	0.73***	1.62***
	(0.01)	(0.03)
Average Test Scores in 8th	1.28***	0.80***
	(0.02)	(0.01)

Failed a Course in 8th	0.77***	1.23***
	(0.02)	(0.03)
Remedial courses in 8th	0.65***	1.21*
	(0.05)	(0.10)
Accelerated courses in 8th	1.34***	0.82***
	(0.04)	(0.03)
GPA in 8th	1.62***	0.67***
	(0.03)	(0.01)
Observations	57209	57137
Pseudo R^2	0.12	0.12

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B3: Results from Logistic Regression with School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.59^{***}	0.59^{***}	0.68^{***}	1.19^{***}	1.17^{***}	0.99
	(0.02)	(0.01)	(0.03)	(0.03)	(0.03)	(0.04)
Black	0.50^{***}			1.76^{***}		
	(0.02)			(0.06)		
Black Credit Recovery Student	0.94			0.98		
	(0.04)			(0.04)		
Hispanic		0.89^{*}			1.05	
		(0.05)			(0.06)	
Hispanic Credit Recovery Student		0.86^{**}			1.07	
		(0.05)			(0.06)	
Economically Disadvantaged			1.50^{***}			0.61^{***}
			(0.06)			(0.02)
Economically Disadvantaged Credit Recovery Student			0.82^{***}			1.25^{***}
			(0.04)			(0.06)
Observations	57137	57137	57137	57209	57209	57209
Pseudo R^2	0.12	0.12	0.12	0.12	0.12	0.12

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B4: Fixed Effects Models Investigating the Association Between the Number of Credit Recovery Courses and the Outcomes

	(2) Grad in Four	(3) Dropout
Credit Recovery Student	1.29***	0.79***
	(0.05)	(0.03)
Number of Credit Recovery Courses	0.96*	0.86***
	(0.02)	(0.02)
Number of Credit Recovery Courses Squared	1.001	0.998
	(0.0004)	(0.004)
Observations	57209	57137
Pseudo R2	0.12	0.12

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C. Students Who Only Failed One Course

Table C1: Balance Check After Matching Process, Max of One Failed Course

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.45	0.50	0.00	1.00
	Not CR	0.45	0.50		
Student is Hispanic	CR	0.15	0.36	0.00	1.00
	Not CR	0.15	0.36		
Student is Other Race	CR	0.08	0.27	0.02	0.96
	Not CR	0.09	0.28		
Student is Female	CR	0.45	0.50	0.06	1.00
	Not CR	0.48	0.50		
Student was Gifted (8th Grade)	CR	0.04	0.20	0.00	1.00
	Not CR	0.04	0.20		
Student was SPED (8th Grade)	CR	0.19	0.39	0.03	1.02
	Not CR	0.18	0.39		
Student was Previously LEP (8th Grade)	CR	0.05	0.22	0.01	1.02
	Not CR	0.05	0.22		
Student was LEP (8th Grade)	CR	0.07	0.25	0.00	1.00
	Not CR	0.07	0.25		
Student is Economically Disadvantaged	CR	0.79	0.41	0.00	1.00
	Not CR	0.79	0.41		
Percent Days Absent (8th Grade)	CR	6.01	5.65	0.02	1.03
	Not CR	5.92	5.48		
Approximate Age (8th Grade)	CR	14.52	0.61	0.01	1.01
	Not CR	14.52	0.60		
Average 8th Test Score (8th Grade)	CR	-0.46	0.73	0.00	0.99
	Not CR	-0.46	0.74		
Failed a Course (8^{th} Grade)	CR	0.30	0.46	0.02	0.99
	Not CR	0.30	0.46		
Took Remedial Course (8th Grade)	CR	0.02	0.14	0.01	0.96
	Not CR	0.02	0.14		
Took Advanced Course (8th Grade)	CR	0.17	0.38	0.04	0.97
	Not CR	0.18	0.39		
GPA (8th Grade)	CR	2.48	0.70	0.05	0.99
	Not CR	2.52	0.71		

Table C2: Results from Logistic Regression with School-by-Cohort Fixed Effects Using a Matched Sample

	(1)	(2)
	Graduate from HS in Four Years	Drop Out
Credit Recovery	1.10	0.64^{***}
	(0.06)	(0.04)
Black	1.84^{***}	0.42^{***}
	(0.13)	(0.03)
Hispanic	1.31^{*}	0.67^{**}
	(0.15)	(0.09)
Other Race	1.20	0.70^{**}
	(0.12)	(0.08)
Female	0.96	1.02
	(0.05)	(0.06)
Gifted in 8^{th}	0.83	1.04
	(0.13)	(0.20)
SPED in 8^{th}	0.92	0.87
	(0.06)	(0.06)
Was LEP in 8^{th}	1.62^{**}	0.51^{***}
	(0.26)	(0.10)
LEP in 8^{th}	1.48^{**}	0.54^{***}
	(0.20)	(0.09)
Economically Disadvantaged	0.64^{***}	1.60^{***}
	(0.05)	(0.14)
Percent Absences in 8^{th}	0.93^{***}	1.07^{***}
	(0.00)	(0.00)
Approximate Age in 8^{th}	0.74^{***}	1.58^{***}
	(0.03)	(0.07)
Average Test Scores in 8^{th}	1.28^{***}	0.78^{***}
	(0.06)	(0.04)

Failed a Course in 8th	0.76***	1.33***
	(0.05)	(0.10)
Remedial courses in 8th	0.72	1.06
	(0.14)	(0.24)
Accelerated courses in 8th	1.18*	0.89
	(0.09)	(0.08)
GPA in 8th	1.52***	0.72***
	(0.08)	(0.04)
Observations	13039	12433
Pseudo R^2	0.10	0.11

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C3: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.65^{***}	0.64^{***}	0.69^{**}	1.17^{*}	1.12^{*}	1.09
	(0.05)	(0.04)	(0.10)	(0.08)	(0.06)	(0.13)
Black	0.43^{***}			1.95^{***}		
	(0.04)			(0.16)		
Black Credit Recovery Student	0.98			0.87		
	(0.12)			(0.09)		
Hispanic		0.66^{**}			1.41^{**}	
		(0.10)			(0.18)	
Hispanic Credit Recovery Student		1.03			0.84	
		(0.18)			(0.12)	
Economically Disadvantaged			1.65^{***}			0.64^{***}
			(0.18)			(0.06)
Economically Disadvantaged Credit Recovery Student			0.93			1.00
			(0.14)			(0.13)
Observations	12433	12433	12433	13039	13039	13039
Pseudo R^2	0.11	0.11	0.11	0.10	0.10	0.10

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D. Students Who Failed the End-of-Course Exam in Math I

Table D1: Balance Check After Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.50	0.50	0.05	1.00
	Not CR	0.47	0.50		
Student is Hispanic	CR	0.17	0.38	0.02	0.98
	Not CR	0.18	0.38		
Student is Other Race	CR	0.05	0.23	0.06	0.90
	Not CR	0.07	0.25		
Student is Female	CR	0.35	0.48	0.08	0.98
	Not CR	0.39	0.49		
Student was Gifted (8th Grade)	CR	0.01	0.09	0.02	0.89
	Not CR	0.01	0.11		
Student was SPED (8th Grade)	CR	0.24	0.43	0.00	1.00
	Not CR	0.24	0.43		
Student was Previously LEP (8th Grade)	CR	0.04	0.20	0.02	0.96
	Not CR	0.05	0.21		
Student was LEP (8th Grade)	CR	0.10	0.30	0.02	0.98
	Not CR	0.11	0.31		
Student is Economically Disadvantaged	CR	0.86	0.34	0.00	1.00
	Not CR	0.86	0.34		
Percent Days Absent (8th Grade)	CR	7.42	6.72	0.01	1.03
	Not CR	7.48	6.54		
Approximate Age (8th Grade)	CR	14.59	0.63	0.02	1.00
	Not CR	14.58	0.63		
Average 8th Test Score (8th Grade)	CR	-0.80	0.68	0.03	0.99
	Not CR	-0.78	0.69		
Failed a Course (8^{th} Grade)	CR	0.48	0.50	0.09	1.01
	Not CR	0.43	0.50		
Took Remedial Course (8th Grade)	CR	0.02	0.15	0.06	1.26
	Not CR	0.01	0.12		
Took Advanced Course (8th Grade)	CR	0.04	0.20	0.01	1.02
	Not CR	0.04	0.20		
GPA (8th Grade)	CR	2.10	0.69	0.10	1.04
	Not CR	2.17	0.67		
Standardized EOC Score	CR	-0.54	0.64	0.01	1.02
	Not CR	-0.53	0.63		

Table D2: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.19**	0.70***
	(0.06)	(0.04)
Black	1.86***	0.47***
	(0.14)	(0.04)
Hispanic	1.20	0.66**
	(0.16)	(0.09)
Other Race	1.00	0.81
	(0.12)	(0.10)
Female	1.27***	0.98
	(0.07)	(0.06)
Gifted in 8th	0.65	1.12
	(0.19)	(0.36)
SPED in 8th	1.09	0.75***
	(0.07)	(0.05)
Was LEP in 8th	1.20	0.90
	(0.21)	(0.17)
LEP in 8th	1.16	0.85
	(0.17)	(0.13)
Economically Disadvantaged	0.74**	1.19
	(0.07)	(0.12)
Percent Absences in 8th	0.93***	1.06***
	(0.00)	(0.00)
Approximate Age in 8th	0.78***	1.59***
	(0.03)	(0.07)
Average Test Scores in 8th	1.18***	0.88**
	(0.05)	(0.04)

Failed a Course in 8th	0.80**	1.20*
	(0.06)	(0.09)
Remedial courses in 8th	0.99	0.65
	(0.21)	(0.15)
Accelerated courses in 8th	1.40*	0.80
	(0.20)	(0.12)
GPA in 8th	1.55***	0.75***
	(0.09)	(0.04)
Standardized EOC Score	1.15**	0.89*
	(0.05)	(0.04)
Observations	7263	7208
Pseudo R^2	0.10	0.09

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D3: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.78**	0.70***	0.69*	1.15	1.18**	1.29
	(0.06)	(0.04)	(0.11)	(0.09)	(0.07)	(0.19)
Black	0.52***			1.81***		
	(0.05)			(0.16)		
Black Credit Recovery Student	0.79*			1.07		
	(0.09)			(0.11)		
Hispanic		0.67**			1.16	
		(0.10)			(0.17)	
Hispanic Credit Recovery Student		0.97			1.07	
		(0.15)			(0.15)	
Economically Disadvantaged			1.18			0.77*
			(0.15)			(0.09)
Economically Disadvantaged Credit Recovery Student			1.01			0.92
			(0.17)			(0.15)
Observations	7208	7208	7208	7263	7263	7263
Pseudo R^2	0.09	0.09	0.09	0.10	0.10	0.10

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E. Students Who Failed the End-of-Course Exam in English II

Table E1: Balance Check After Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.51	0.50	0.09	1.00
	Not CR	0.46	0.50		
Student is Hispanic	CR	0.20	0.40	0.06	0.96
	Not CR	0.23	0.42		
Student is Other Race	CR	0.07	0.25	0.02	1.03
	Not CR	0.06	0.24		
Student is Female	CR	0.33	0.47	0.07	1.03
	Not CR	0.30	0.46		
Student was Gifted (8th Grade)	CR	0.03	0.18	0.08	1.28
	Not CR	0.02	0.14		
Student was SPED (8th Grade)	CR	0.22	0.42	0.04	0.97
	Not CR	0.24	0.43		
Student was Previously LEP (8th Grade)	CR	0.06	0.23	0.05	1.11
	Not CR	0.05	0.21		
Student was LEP (8th Grade)	CR	0.11	0.32	0.07	0.93
	Not CR	0.14	0.34		
Student is Economically Disadvantaged	CR	0.89	0.31	0.00	1.00
	Not CR	0.89	0.31		
Percent Days Absent (8th Grade)	CR	6.61	5.88	0.00	1.05
	Not CR	6.61	5.60		
Approximate Age (8th Grade)	CR	14.57	0.62	0.06	0.97
	Not CR	14.61	0.65		
Average 8th Test Score (8th Grade)	CR	-0.65	0.76	0.01	0.98
	Not CR	-0.66	0.78		
Failed a Course (8^{th} Grade)	CR	0.44	0.50	0.01	1.00
	Not CR	0.44	0.50		
Took Remedial Course (8th Grade)	CR	0.03	0.17	0.02	0.95
	Not CR	0.03	0.18		
Took Advanced Course (8th Grade)	CR	0.14	0.35	0.00	1.00
	Not CR	0.14	0.35		
GPA (8th Grade)	CR	2.20	0.70	0.00	1.02
	Not CR	2.20	0.69		
Standardized EOC Score	CR	-0.83	0.79	0.01	1.00
	Not CR	-0.84	0.79		

Table E2: Results from Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.44***	0.60***
	(0.09)	(0.04)
Black	1.61***	0.53***
	(0.16)	(0.06)
Hispanic	1.07	0.81
	(0.15)	(0.13)
Other Race	1.07	0.82
	(0.15)	(0.13)
Female	1.14	1.00
	(0.08)	(0.08)
Gifted in 8th	0.94	1.36
	(0.22)	(0.35)
SPED in 8th	1.01	0.86
	(0.08)	(0.08)
Was LEP in 8th	1.26	0.62*
	(0.24)	(0.14)
LEP in 8th	1.15	0.83
	(0.17)	(0.14)
Economically Disadvantaged	0.70**	1.52**
	(0.09)	(0.24)
Percent Absences in 8th	0.94***	1.06***
	(0.01)	(0.01)
Approximate Age in 8th	0.86**	1.35***
	(0.05)	(0.08)
Average Test Scores in 8th	1.00	1.08
	(0.06)	(0.07)

Failed a Course in 8th	0.80*	1.14
	(0.07)	(0.11)
Remedial courses in 8th	0.67	1.10
	(0.14)	(0.26)
Accelerated courses in 8th	1.24	0.80
	(0.14)	(0.11)
GPA in 8th	1.63***	0.73***
	(0.11)	(0.06)
Standardized EOC Score	1.45***	0.73***
	(0.09)	(0.05)
Observations	5036	4768
Pseudo R^2	0.10	0.08

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table E3: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.62^{***}	0.59^{***}	0.66	1.52^{***}	1.46^{***}	1.17
	(0.06)	(0.05)	(0.16)	(0.14)	(0.11)	(0.24)
Black	0.55^{***}			1.69^{***}		
	(0.07)			(0.19)		
Black Credit Recovery Student	0.92			0.90		
	(0.14)			(0.12)		
Hispanic		0.80			1.10	
		(0.14)			(0.18)	
Hispanic Credit Recovery Student		1.05			0.94	
		(0.19)			(0.15)	
Economically Disadvantaged			1.60^{*}			0.63^{**}
			(0.31)			(0.10)
Economically Disadvantaged Credit Recovery Student			0.90			1.25
			(0.23)			(0.27)
Observations	4768	4768	4768	5036	5036	5036
Pseudo R^2	0.08	0.08	0.08	0.10	0.10	0.10

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

F. Students Who Failed the End-of-Course Exam in Biology

Table F1: Balance Check After Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.49	0.50	0.03	1.00
	Not CR	0.47	0.50		
Student is Hispanic	CR	0.20	0.40	0.04	0.97
	Not CR	0.22	0.42		
Student is Other Race	CR	0.07	0.25	0.06	1.13
	Not CR	0.05	0.22		
Student is Female	CR	0.36	0.48	0.06	0.98
	Not CR	0.39	0.49		
Student was Gifted (8th Grade)	CR	0.01	0.12	0.08	0.76
	Not CR	0.03	0.16		
Student was SPED (8th Grade)	CR	0.24	0.43	0.03	1.02
	Not CR	0.23	0.42		
Student was Previously LEP (8th Grade)	CR	0.06	0.24	0.05	1.09
	Not CR	0.05	0.22		
Student was LEP (8th Grade)	CR	0.12	0.33	0.06	0.93
	Not CR	0.14	0.35		
Student is Economically Disadvantaged	CR	0.88	0.33	0.00	1.00
	Not CR	0.88	0.33		
Percent Days Absent (8th Grade)	CR	6.37	5.38	0.06	1.03
	Not CR	6.05	5.24		
Approximate Age (8th Grade)	CR	14.61	0.65	0.02	1.03
	Not CR	14.60	0.63		
Average 8th Test Score (8th Grade)	CR	-0.75	0.69	0.05	0.95
	Not CR	-0.71	0.73		
Failed a Course (8th Grade)	CR	0.44	0.50	0.09	1.02
	Not CR	0.39	0.49		
Took Remedial Course (8th Grade)	CR	0.02	0.14	0.02	1.06
	Not CR	0.02	0.13		
Took Advanced Course (8th Grade)	CR	0.10	0.30	0.06	0.92
	Not CR	0.12	0.32		
GPA (8th Grade)	CR	2.22	0.67	0.11	0.95
	Not CR	2.29	0.70		
Standardized EOC Score	CR	-0.67	0.74	0.00	1.16
	Not CR	-0.67	0.63		

Table F2: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.16*	0.59***
	(0.08)	(0.05)
Black	2.14***	0.36***
	(0.21)	(0.04)
Hispanic	1.25	0.74
	(0.19)	(0.14)
Other Race	1.10	0.66*
	(0.16)	(0.13)
Female	1.42***	0.90
	(0.10)	(0.08)
Gifted in 8th	0.96	1.06
	(0.25)	(0.33)
SPED in 8th	1.05	0.81*
	(0.08)	(0.08)
Was LEP in 8th	1.17	0.74
	(0.22)	(0.18)
LEP in 8th	1.25	0.70
	(0.20)	(0.14)
Economically Disadvantaged	0.67**	1.44*
	(0.08)	(0.23)
Percent Absences in 8th	0.95***	1.05***
	(0.01)	(0.01)
Approximate Age in 8th	0.91	1.39***
	(0.05)	(0.09)
Average Test Scores in 8th	0.90	1.13
	(0.05)	(0.08)

Failed a Course in 8th	0.74***	1.30*
	(0.06)	(0.14)
Remedial courses in 8th	0.44**	1.17
	(0.11)	(0.36)
Accelerated courses in 8th	1.24	0.91
	(0.15)	(0.14)
GPA in 8th	1.69***	0.69***
	(0.12)	(0.06)
Standardized EOC Score	1.14*	0.92
	(0.06)	(0.06)
Observations	4920	4452
Pseudo R^2	0.08	0.09

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table F3: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.66***	0.56***	0.92	1.08	1.22**	0.79
	(0.07)	(0.05)	(0.22)	(0.10)	(0.09)	(0.15)
Black	0.39***			2.01***		
	(0.05)			(0.23)		
Black Credit Recovery Student	0.78			1.16		
	(0.13)			(0.15)		
Hispanic		0.68			1.37	
		(0.14)			(0.23)	
Hispanic Credit Recovery Student		1.22			0.81	
		(0.24)			(0.13)	
Economically Disadvantaged			1.78**			0.55***
			(0.35)			(0.09)
Economically Disadvantaged Credit Recovery Student			0.61			1.54*
			(0.16)			(0.31)
Observations	4452	4452	4452	4920	4920	4920
Pseudo R^2	0.09	0.09	0.09	0.08	0.08	0.08

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

G. Students Who Failed One or More EOC Courses, Combined

Table G1: Balance Check After Matching Process

Variable		Mean	SD	Standardized Differences	SD Ratio
Student is Black	CR	0.47	0.50	0.01	1.00
	Not CR	0.47	0.50		
Student is Hispanic	CR	0.18	0.39	0.04	1.03
	Not CR	0.17	0.38		
Student is Other Race	CR	0.06	0.24	0.02	1.05
	Not CR	0.06	0.23		
Student is Female	CR	0.35	0.48	0.05	0.99
	Not CR	0.38	0.48		
Student was Gifted (8th Grade)	CR	0.02	0.14	0.02	1.08
	Not CR	0.02	0.13		
Student was SPED (8th Grade)	CR	0.23	0.42	0.02	1.01
	Not CR	0.22	0.42		
Student was Previously LEP (8th Grade)	CR	0.05	0.22	0.05	1.12
	Not CR	0.04	0.20		
Student was LEP (8th Grade)	CR	0.10	0.31	0.01	1.01
	Not CR	0.10	0.30		
Student is Economically Disadvantaged	CR	0.84	0.36	0.00	1.00
	Not CR	0.84	0.36		
Percent Days Absent (8th Grade)	CR	6.80	6.03	0.02	1.02
	Not CR	6.70	5.92		
Approximate Age (8th Grade)	CR	14.58	0.63	0.03	1.01
	Not CR	14.59	0.63		
Average 8th Test Score (8th Grade)	CR	-0.70	0.72	0.00	1.00
	Not CR	-0.69	0.72		
Failed a Course (8^{th} Grade)	CR	0.45	0.50	0.07	1.01
	Not CR	0.41	0.49		
Took Remedial Course (8th Grade)	CR	0.02	0.15	0.02	1.08
	Not CR	0.02	0.14		
Took Advanced Course (8th Grade)	CR	0.10	0.30	0.03	1.04
	Not CR	0.09	0.28		
GPA (8th Grade)	CR	2.19	0.70	0.08	1.01
	Not CR	2.24	0.69		
Standardized EOC Score	CR	-0.63	0.64	0.02	0.96
	Not CR	-0.64	0.66		

Table G2: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample

	(1) Graduate from HS in Four Years	(2) Drop Out
Credit Recovery	1.21***	0.60***
	(0.04)	(0.02)
Black	1.82***	0.47***
	(0.09)	(0.02)
Hispanic	1.25**	0.73***
	(0.10)	(0.06)
Other Race	1.02	0.86
	(0.07)	(0.07)
Female	1.32***	0.93
	(0.05)	(0.04)
Gifted in 8^{th}	0.86	1.09
	(0.12)	(0.17)
SPED in 8^{th}	1.10*	0.79***
	(0.04)	(0.04)
Was LEP in 8^{th}	1.07	0.76*
	(0.11)	(0.09)
LEP in 8^{th}	1.15	0.72***
	(0.10)	(0.07)
Economically Disadvantaged	0.75***	1.22***
	(0.04)	(0.07)
Percent Absences in 8^{th}	0.93***	1.06***
	(0.00)	(0.00)
Approximate Age in 8^{th}	0.82***	1.52***
	(0.02)	(0.04)
Average Test Scores in 8^{th}	1.09**	0.95
	(0.03)	(0.03)

Failed a Course in 8th	0.77***	1.21***
	(0.03)	(0.06)
Remedial courses in 8th	0.59***	0.99
	(0.08)	(0.14)
Accelerated courses in 8th	1.37***	0.78***
	(0.09)	(0.06)
GPA in 8th	1.56***	0.72***
	(0.05)	(0.03)
Standardized EOC Score	1.23***	0.93*
	(0.04)	(0.03)
Observations	19196	19109
Pseudo R^2	0.09	0.09

Exponentiated coefficients; standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table G3: Results From Logistic Regression With School-by-Cohort Fixed Effects Using a Matched Sample by Race and Socioeconomic Status

	(1) Drop Out	(2) Drop Out	(3) Drop Out	(4) Grad in Four	(5) Grad in Four	(6) Grad in Four
Credit Recovery Student	0.65^{***}	0.59^{***}	0.70^{***}	1.18^{***}	1.22^{***}	1.02
	(0.03)	(0.02)	(0.07)	(0.05)	(0.04)	(0.09)
Black	0.51^{***}			1.79^{***}		
	(0.03)			(0.10)		
Black Credit Recovery Student	0.83^{*}			1.04		
	(0.06)			(0.07)		
Hispanic		0.70^{***}			1.30^{**}	
		(0.07)			(0.11)	
Hispanic Credit Recovery Student		1.09			0.92	
		(0.10)			(0.08)	
Economically Disadvantaged			1.32^{***}			0.69^{***}
			(0.10)			(0.05)
Economically Disadvantaged Credit Recovery Student			0.84			1.22^{*}
			(0.09)			(0.11)
Observations	19109	19109	19109	19196	19196	19196
Pseudo R^2	0.09	0.09	0.09	0.09	0.09	0.09

Exponentiated coefficients; Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$