A Choice Between Second Chances: An Analysis of How Students Address Course Failure

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Abstract

Purpose

On average, one in five high school students in North Carolina fails at least one core, required course every year. After failure, students have two options to regain course credit: repeat the course face-to-face (F2F) or online credit recovery (OCR). This study seeks to provide descriptive evidence on OCR/F2F enrollment patterns over time and across schools.

Research Methods

The data include administrative records from the state of North Carolina on all high school students enrolled in public schools between the 2012-13 and 2016-17 school years. Analyses are descriptive with ordinary least squares regression and multilevel models.

Findings

OCR has grown in popularity: schools, on average, were as likely to enroll students in OCR as F2F courses by 2015-16. Increasing high school graduation rates and decreasing test score proficiency are correlated with increasing OCR enrollment at the school level. Students with more absences and Black students are more likely to enroll in OCR, and students with disabilities are less likely to enroll. OCR enrollment is associated with a 12 percentage point increase in the probability of earning course credit over F2F courses although this could indicate students more likely to earn course credit are assigned to OCR.

Implications

School leaders should consider how they assign students to OCR/F2F given the findings indicating OCR enrollment could come with intended benefits for credit earning with unintended negative consequences for test scores. Future research could explore these processes to understand the most effective uses of OCR for student remediation of course credit.

KEYWORDS: high school, course failure, descriptive research, online learning, online credit recovery

Author Biography

Samantha Viano is an Assistant Professor in the College of Education and Human Development at George Mason University. Dr. Viano's research focuses on evaluating policies and assessing school contexts that predominantly affect minoritized student populations and their teachers including policies on school safety and security, online credit recovery, teacher retention, and methods for studying racial equity.

Failing courses in high school is a commonly cited reason why students do not graduate (Allensworth and Easton 2005; Bowers 2010; Neild et al. 2008). Traditionally, students who failed courses could regain the lost credit by repeating the course in full with a face-to-face instructor. Students now have another option: online credit recovery (OCR). OCR refers to online courses specifically designed for students who have previously failed a traditional (i.e., face-to-face or F2F) version of that course. OCR 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.

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 OCR courses that are used as an easy way to graduate more students (Gardner 2016; Turner 2015). These media sources accuse schools and districts of funneling struggling students into OCR 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.

Several recent studies strongly suggest that OCR has become a staple offering in high schools around the U.S, but descriptive evidence thus far has lacked a comprehensive view of course failure and credit recovery options. For instance, a nationwide survey in the 2014-15 school year indicated that about 89% of school districts offered at least one credit recovery course with 71% of schools offering OCR and 42% of schools offering F2F credit recovery. The survey also indicated that about 15% of high school students were enrolled in at least one credit recovery course, but this percentage does not reflect if students were enrolled in an OCR or F2F course and lacked information on the percentage of students who failed courses in the school

(“Issue Brief: Credit Recovery” 2018). Surveys from Iowa, Wisconsin, New York, North Carolina and Montana confirm that credit recovery, in general, is common in high schools and OCR is a popular reason that schools are expanding online learning options but lacked information on OCR and F2F enrollment (Clements, Stafford et al. 2015; Clements, Zweig et al. 2015; Stallings et al. 2016; Stevens et al. 2016). These studies often did not clearly differentiate enrollment between F2F and OCR courses, leading to inconsistent evidence on the prevalence of OCR. In addition, they lacked comparisons between OCR enrollment rates and student course failure rates such that it is unclear what proportion of the eligible population accessed OCR.

This study seeks to address this gap in the descriptive evidence on credit recovery by directly comparing enrollment in OCR versus F2F courses for students who fail courses while taking a longitudinal perspective to understand if OCR has become as popular as the media has portrayed it to be. This study seeks to provide much needed information to better understand two key issues: course failure remediation options in high school and OCR popularity. Despite course failure consistently predicting dropping out of school, the nascent literature base has mostly overlooked basic questions about the likelihood of regaining course credit once a student fails a course, the options for regaining course credit, and which students are most likely to be enrolled in the various options. This study seeks to fill this gap in the literature by examining the correlates based on how students attempt to remediate their lost course credit. While course failure in high school is an old problem, OCR is a new solution. Understanding the popularity of OCR compared to other options for addressing course failure is an important step toward understanding how schools are using OCR courses. This study will address the following research questions:

1. When students fail a core course required for high school graduation, how often did they repeat the course F2F, take the course through OCR, do neither, or do both?
2. To what extent have the ways in which schools addressed course failure varied across schools and changed over time?
3. To what extent are school-level enrollment rates in OCR associated with school-level characteristics?
4. To what extent does a student's enrollment in OCR versus F2F courses correlate with the student's characteristics?
5. Descriptively, how likely are students to earn course credit if they repeat a course F2F, take an OCR course, do neither, or do both?

Course Failure in High School

Failing courses in high school is, by design, a key barrier preventing many students from graduating from high school since state-level policies typically require a certain number of credits to graduate. Prior research confirms that failing courses or low credit accumulation leads to lower probability of high school graduation (Bowers 2010; Mac Iver 2011; Neild et al. 2008; Silver et al. 2008; Allensworth and Easton 2005).

Despite the commonplace nature of course failure, or perhaps because of it, very little research has critically examined course failure in high school. Failing a course is used as a common predictor of whether a student graduates from or drops out of high school, but it is difficult to find studies that focus on the prevalence, causes, consequences, and remedies for failing courses. A couple of recent studies have used data mining techniques to build models predicting academic failure, finding test scores, age, motivation, disability status and smoking habits predicted course failure (Márquez-vera et al. 2013) as well as failing a course previously and grades (Teshnizi and Ayatollahi 2015).

Course failure is part of a broader system of personal and structural barriers many students face when seeking a high school diploma. In a review of the literature on dropping out of high school, Dupéré and colleagues (2014) proposed a developmental timeline of different types of factors that lead to drop out. In their integrative *stress process life course model of dropout*, individual, family, neighborhood, and peer characteristics as well as turning points (e.g., teen parenting, financial hardship) are connected to dropping out of high school through *proximal mediators* – students' actions that lead to dropping out (Dupéré et al. 2015).

All of the points on the developmental timeline flow through proximal mediators, specific causes of dropping out such as engagement, achievement, and behavior. In this model, failing classes and the lack of course credit accumulation are potential proximal mediators. Leading to these proximal mediators are *predisposing factors*, *precipitating factors*, *contextual exposure*, and *protective factors*. Predisposing factors are individual characteristics that make someone vulnerable to dropout based on a vulnerability-stress model of psychopathy including genetic factors and personality traits as well as developmental pathways from a life course perspective (Hankin 2012; Alexander et al. 2001). Turning points or stressors including divorce, incarceration and other life events act as precipitating factors (Amato 2010; Kirk and Sampson 2013; Johnson et al. 2011). The other category of risk of dropout includes broader geographic and historical contextual influences like neighborhood poverty and the local labor market (Lawson and Lawson 2013; Johnson Jr 2010; Leventhal et al. 2009). Students can also be resilient against dropout based on their internal resources like identity and goals as well as external resources like those in schools or families (Tinto 1993). This framework has each of the factors leading into the proximal mediators, interacting with each other bi-directionally, allowing for the risk factors to be addressed by protective factors like school-level policies that help students to graduate high school. Students who fail courses can be protected from dropout or have dropout risk exacerbated by predisposing or precipitating factors or contextual exposure.

How Students Address Course Failure in High School

Schools have traditionally offered students a second chance to earn credit for a course they failed. Students might repeat the course they failed (during the school year or over the summer) or be retained to repeat the grade in full (although this is a less common solution in high schools than in lower grades). OCR has increasingly become available to high schools, as schools build their technological capabilities and with the expansion of high-speed internet access (Watson et al. 2008). Within the Dupéré et al. (2015) framework, course remediation options are part of the protective factors that can help students to avoid dropout, lessening proximal mediators like course failure. Below, I review the literature on OCR and F2F courses.

Face-to-Face Credit Recovery

Despite the historical ubiquity of summer school and repeating courses, only one available study examined the prevalence of F2F courses and the effectiveness of F2F course on regaining credit for that course. This study was of a large high school district in California and focused on students who had failed Algebra I, finding that 44% of students repeated Algebra I F2F. Almost three-quarters of students repeating Algebra I passed the course the second time they enrolled (Fong et al. 2014). While many studies examine the efficacy of summer school with relation to academic achievement, often explicitly examining summer school's effect on summer learning loss, few studies examine the effect of F2F courses on regaining credit.

With little empirical information on F2F credit recovery, some assumptions can be made about how these courses are offered and what it is like to take a F2F credit recovery course. F2F courses will take on the same cost associated with first time course enrollment when courses are repeated during the school year with potentially substantial extra costs when courses are offered over the summer or in the evening. Costs include hiring a certified teacher for the course and associated facilities' costs. F2F courses are likely rather inflexible, having to fit into a student's course schedule or take place when school is not in session when instructors are available. Students likely take F2F courses at the school they regularly attend, although this might differ based on context. Since F2F courses, by definition, take place in a typical setting, they likely have the expected range of content, pedagogical approaches, and assessments. Despite F2F courses being in use for much longer than OCR, there are more empirical studies that address these types of basic questions about OCR enrollment, costs, and the student experience in OCR.

Online Credit Recovery

OCR offers several appealing attributes in contrast to F2F courses. OCR can be offered in a very flexible format with relatively easy expansion capabilities. Schools have the option of offering OCR at any time in any location, thus making it simple for students to recover course credit on their own schedules potentially without interfering with carrying a normal course load, although schools can choose to offer OCR during the school day. Students also might be able to complete online courses faster than traditional courses (Darling-Aduana 2019), which would allow for the students to take more than one OCR course within the same amount of time it would take to repeat a course traditionally.

A nascent literature base has explored the popularity of OCR as well as the costs, implementation, and experiences of those involved in OCR courses. Expansion of the number of students enrolled in OCR comes at some cost to the school district; however, this cost is considered to be less than hiring more teachers to teach additional courses (Murin et al. 2015). Some public providers of OCR 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 OCR students, and/or have a monitor who is a certified teacher (e.g., Frazelle 2016).

OCR course flexibility can range from the traditional constraints of being offered within the school day to the flexibility of being available for students to complete the course at their own pace anytime, anywhere (Murin et al. 2015). We know little about the extent to which these various OCR formats are used. Prior statewide surveys from Iowa and Wisconsin in 2012-13 have found most online courses to be synchronous with a class monitor (Clements, Stafford et al. 2015). A study of schools with successful OCR programs in Montana found schools with high OCR pass rates tended to have their OCR courses during a specific time and place within the regular school day with a certified teacher as facilitator (Frazelle 2016). A nationwide survey from 2015-16 found that 84% of schools offered credit recovery during the school day and over half of schools offered credit recovery outside of regular school hours ("Issue Brief: Credit Recovery" 2018).

OCR can be offered through statewide virtual schools, district virtual schools, or private providers. As of 2016, 24 states had state-run online course providers, which are designed to offer online courses to students enrolled in traditional brick-and-mortar schools (Gemin and Pape 2017). The largest state-run virtual course provider was in Florida and enrolled over 377,000 students in 2013-14, followed by North Carolina Virtual Public School (NCVPS) which enrolled about 105,000 students in online courses the same year. Many large school districts also have their own in-house providers of online courses (Watson et al. 2008). For-profit companies are popular OCR providers 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 by former executives at Apple and Microsoft, and claimed on their website that their online course enrollments in 2014-15, including OCR, reached over two million (“Apex Learning - About Us” n.d.). However, more detailed information on the use of private providers of OCR courses is difficult to find (see Stallings et al. 2016).

Several previous studies have explored OCR enrollment patterns at the student or school level. A report on students enrolled in the Montana Digital Academy found that OCR students were more likely to be male and enrollments were higher in 10^{th} and 11^{th} grade than in 9^{th} or 12^{th} grade. Most course enrollments were in English courses with an overall pass rate of 57% for OCR courses (Stevens et al. 2016). A study of credit recovery in NC between 2008-09 and 2011-12 also found that the same pattern of credit recovery enrollments by grade level, with course enrollments higher for math courses than English courses. Black students were more likely to enroll in credit recovery, accounting for around 45% of credit recovery enrollments (Stallings et al. 2016).

Comparisons Between Face-to-Face and Online Credit Recovery

Several prior studies have compared OCR with F2F courses. A randomized control trial study found that students in Algebra I summer OCR courses in Chicago from one private course provider were less likely to receive course credit than students assigned to F2F summer school courses, although there was no difference in high school graduation rates or credit accumulation between the two samples (Rickles et al. 2018). A study using administrative data from Florida found students in OCR courses were more likely to pass the course and persist to 12th grade than students in F2F courses (Hart et al. 2019). The third study focused on NCVPS OCR courses, finding non-NCVPS OCR and F2F courses, during the time period they studied, were much more common than taking NCVPS OCR courses (Stallings et al. 2016). NCVPS OCR students had lower scores and were less likely to pass an end-of-course exam than the comparison. The most recent year in all of these studies was the 2011-12 school year.

Contribution

This study builds on this literature base in several ways. First, prior studies have typically only examined one OCR provider such that the comparison group in the non-experimental studies often included students enrolled in OCR through private providers. In this study, the comparison group is students who repeated courses F2F. Second, these studies gave little attention to overall enrollment patterns such that there remains scant descriptive information about OCR enrollment patterns and correlates. Third, this study will address questions about the overall prevalence of OCR compared to course failure rates, estimates that help to put results of other OCR studies into context. Fourth, this study includes OCR coursetaking in more recent years, which is noteworthy as online courses continue to expand their reach and technology becomes more available.

This study is intended to complement recent work on the effects of OCR on student outcomes. The research described above using experiments and causal identification strategies to identify if OCR helps students to graduate from high school, decreases test scores, and other student-level outcomes is important work on the efficacy of OCR. While learning more about whether OCR is effective is important for future policy decision making, descriptive evidence on

OCR helps us to understand how OCR is currently being used. Instead of addressing whether OCR is working, this study seeks to understand the context in which OCR is being implemented.

Traditional Face-to-Face and Online Credit Recovery in North Carolina Public Schools

NC is a particularly relevant state for a descriptive study on OCR. Just like in all states (Tyner and Munyan-Penney 2018), when students fail courses in a NC Public Schools they can remediate the credit through a F2F or OCR course (it has become rare in NC for students to have the option of F2F outside of the regular school year; Weiss and Stallings 2015). In F2F courses, students typically retake the course during the school day, placed in a classroom with students who are taking the course for the first time. The main options for OCR include (a) courses offered through NCVPS, (b) district-based virtual schools (in two school districts), and (c) private providers, by far the most popular option (author’s analysis). This is similar to at least 24 other states that have a state-run provider and allow districts to contract with private vendors (Gemin and Pape 2017). While districts have the option of offering courses through the public provider, NCVPS, at least 87% of districts in NC have contracts with private OCR providers, including Apex, Edmentum/PLATO, and Odysseyware (Stallings et al. 2016).

The NC State Board of Education adopted several official policies on OCR courses. Officially, OCR 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), focusing on deficiencies in the student’s learning. OCR courses are offered as pass/fail and do not factor into students’ GPA. To earn a new grade, students must repeat the course F2F. The length of OCR 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 OCR courses they take. Students take the official state end-of-course exam upon completion of the OCR course, when applicable (Garland et al. 2010).

No regulations require OCR courses to have a certified teacher, instructor, monitor, or any supervision for the courses. This leave open the possibility for a wide range of approaches to instruction and assessment ranging from the NCVPS model which has a certified teacher as the online instructor for all courses ("North Carolina Virtual Public School," n.d.) to fully asynchronous courses completely monitored by software – with automated module selection and grading. Based on interviews with school district officials in North Carolina, some school districts using fully asynchronous courses require the courses to be audited by a certified teacher (sometimes in person during a specified time of the day) or an aide while others have no systematic monitoring procedures for the courses.

Methods

Data and Sample

The data for this study comes from NC, a particularly good site to study OCR because the state is diverse socioeconomically, racially, and in regards to urbanicity while also having a similar configuration of OCR options as other states (Gemin and Pape 2017; Tyner and Munyan-Penney 2018). The data are longitudinal student-level records including all students enrolled in public schools in NC. Student-course roster and grade records identify students who have enrolled in OCR or F2F. These files also identify specific course enrollments (e.g., Math I, English II). In order to investigate student and school characteristics associated with OCR or F2F enrollment, I compiled several data files with information on demographics, academic performance, and attendance at the student and school-level.

The base unit of analysis is at student-course level (although measures are often aggregated to the school level). Each record represents each course 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 they 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., 9th-12th grade) between the 2012-13 and 2016-17 school years (I will henceforth refer to years based on the calendar year during the spring semester such that, for instance, 2015-16 will be written as 2016). In order to more accurately observe course taking patterns over time, I restrict the sample to only student-course records the year the course was originally failed and one year following, avoiding the estimates being affected by how long students had in the data to retake courses (e.g., a student in 2013 would have four years while a student who failed a course in 2017 would less than a year). This restriction eliminates 17.34% of the course records that represented courses that were retaken more than one year after initial failure and courses originally failed in 2017.[2]

Measures

The key measure is how students responded to course failure: OCR or F2F. To create this measure, the first task is to identify which course enrollments are associated with failing for core, required courses using students' grades and course roster information. F2F 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. Because no single variable or procedure can identify all OCR courses, I follow a multistep process to identify OCR courses. First, NC rosters have a course code indicating a course was an OCR course. However, I found notable rates of noncompliance with the course coding system, so I identify OCR courses in several other ways. Based on state-level rules, I identify a course as OCR when students had previously failed a course and retook the course online, as indicated through course codes (a separate course code indicates online enrollment) and course titles. OCR courses are also identified through grades, where a grade of a "pass" or "fail" indicates an OCR course because only OCR courses are graded on a pass/fail basis, according to state-level rules. After assigning individual course enrollments to OCR or F2F, this measure is aggregated to the student-course level (i.e., the unit of analysis) to indicate if the student-course record is ever associated with OCR or F2F enrollment. Consequently, student-course records are identified as OCR, F2F, both (i.e., if students took the course through OCR and F2F), or neither (i.e., they did not remediate the course after failing within this time period).

In order to answer research questions (3), (4), and (5), the dataset includes a rich set of covariates as independent variables. Referring to the stress process life course model of dropout (Dupéré et al. 2015), these covariates include predisposing, protective, and contextual exposure factors (the nature of the data do not allow for the inclusion of measures of precipitating factors). Financial information is available at the school-level, indicating different financial resources available to the school. In high school, students take end-of-course exams (EOC) in Math I, Biology, and English II. The lagged proficiency rates on EOCs at the school level are 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 helps to assess whether schools respond to the graduation rate through placing more or less students in OCR. These three measures are also protective factors as they indicate when schools include a high-performing student body or have more financial resources. The lagged course failure rate indicates the percentage of first-time, core-course enrollments that result in failure, a potential measure of contextual exposure since exposure to more students failing courses could make a student more at risk for failure (the converse is also possible; Gaviria and Raphael 2001). Schools might also be responding to higher course failure rates by increasing their OCR enrollment the following school year. Other school-level variables that are potential contextual exposure factors include the percent of teachers with three years of experience or less, suspension rates, violent acts rate, and the lagged chronic absenteeism rate. Potential protective factors (i.e., that could help prevent dropout) include the percentage of teachers with National Board Certification and school type (magnet or alternative). Other school-level covariates include school urbanicity, enrollment, and percent of the student body by race/ethnicity or special categories – limited English proficient (LEP), special education (SPED), and economic disadvantage (ED).

Student-level covariates are available on an annual basis and includes student race/ethnicity, whether the student is or was designated as LEP, whether the student is classified as ED, and whether the student has an individualized educational plan (IEP). These covariates are predisposing factors, indicating 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 Hispanic or Black—are more or less likely to be in OCR. Another indicator of a potential predisposing factor is percentage of days the student was absent in a given school year. Protective factors include whether the student is gifted and whether they are female. Students' middle school academic performance is also considered a protective factor in this model, which I measure as average scores on the end-of-grade tests given in 8th grade (standardized by test and year), to see whether past higher performance is associated with how a student addresses course failure in high school.

The fifth research question descriptively looks at whether or not students gain credit for a course they previously failed. A student has gained credit for such a course if their course enrollment is associated with a numeric or letter grade above failing or a grade of "pass."

Variables measuring the prevalence of OCR in a school are necessary to answer research questions (2) and (3). These measures are created by using the year a student failed a class, assessing whether they retook that course within the year they failed or the year following their failure through OCR, F2F, both, or neither. This is then scaled up to the school level such that, for instance, the percent OCR in a school in 2016 represents the percent of core courses failed in that school in 2016 that were then taken through OCR in the 2016 or 2017.

Empirical Framework

The first research question for the study asks how often students who fail courses attempt to remediate the credit through F2F, OCR, both, or neither. The second research question asks about OCR/F2F enrollment variation across schools and over time. In order to answer these two questions, I report percentages and show bar charts on enrollment across schools over time. Calculations comparing changes over time reflect differences between courses failed in the 2013 and 2016 school years.

To assess whether school-level enrollment rates are associated with school characteristics, the third research question, I fit an ordinary least squares regression model with percent of failed courses retaken through OCR as the outcome. The unit of analysis for this model is at the school-year level and standard errors are clustered by school. I iteratively add covariates to this model by the variable groupings of school characteristics, contextual exposure, and protective factors before including all covariates in the same model. The final model includes all covariates and the percent of failed courses taken F2F to assess the relationship between F2F enrollment and OCR enrollment.

The fourth research question asks whether enrolling in F2F or OCR is correlated with student characteristics. A multilevel linear probability model answers this research question. The model is multilevel because student-course records are clustered within students and students are clustered within schools, resulting in three levels.[3]

$$\mu_{ijk} = \gamma_{000} + \gamma_{100} Math_{ijk} + \gamma_{200} Science_{ijk} + \gamma_{300} SocialStudies_{ijk} + \gamma_{400} Year_{ijk} + \boldsymbol{\gamma_{0y0} StudentCovariates_{jk}} + \boldsymbol{\gamma_{00z} SchoolCovariates_{k}} + u_{0jk} + u_{00k} + e_{ijk}$$

The outcome μ_{ijk} is whether the student-course *i*, for student *j*, in school *k* enrolled exclusively in OCR (μ_{ijk} =1) or F2F (μ_{ijk} =0).[4] The student-course level covariates are the course subject and year the student originally failed the course. The student-level covariates listed in the Measures section will be in the model and are represented by the vector $\boldsymbol{StudentCovariates_{jk}}$. The model also includes the school-level covariates, $\boldsymbol{SchoolCovariates_{k}}$, to hold constant these fixed effects. The model also includes random effects at the student (u_{0jk}) and school (u_{00k}) levels as well as an error term (e_{ijk}). I will explore the resulting student-course and student-level coefficients from the model both for their statistical as well as practical significance to see if there is any indication that OCR is systematically being used for some students, potentially based on predisposing or protective risk factors, over others.

The fifth research question asks if F2F, OCR, both, or neither is associated with gaining credit for a course. To answer this research question, I estimate the following multilevel linear probability model,

$$\mu_{ijk} = \gamma_{000} + \gamma_{100}OCR_{ijk} + \gamma_{200}OCR\&F2F_{ijk} + \gamma_{300}Neither_{ijk} + \gamma_{400}Math_{ijk} + \gamma_{500}Science_{ijk} + \gamma_{600}SocialStudies_{ijk} + \boldsymbol{\gamma_{x00}Year_{ijk}} + \boldsymbol{\gamma_{0y0}StudentCovariates_{jk}} + \boldsymbol{\gamma_{00z}SchoolCovariates_{k}} + u_{0jk} + u_{00k}$$

This is the same model as the one addressing the fourth research question with a couple of changes. First, the outcome, μ_{ijk}, is gaining credit for the previously-failed course. Second, three terms measuring enrollment in OCR, OCR&F2F, and Neither are added at the student-course level, making the comparison F2F only. I also estimate the model with a series of interactions between OCR and selected student covariates. In the stress process life course model, students' risk of dropping out is a combination of many factors. If OCR is truly a protective factor helping to prevent dropout, then it might be particularly effective for students who would traditionally struggle to succeed after a setback like failing courses. Therefore, I explore a variety of interactions between OCR and contextual risk factors including students who identify as Black or Hispanic, ED students, students with IEPs, students identified as LEPs and the protective factor of 8th grade test scores. I fit six separate models interacting one of these covariates with OCR and then one model with all of these interactions.

Note that the results of this model are descriptive. There are many reasons why students enrolling in OCR might be more likely to earn course credit than F2F students other than the courses themselves. For instance, schools might be purposefully limiting OCR enrollment to those who are most likely to re-earn course credit. This analysis remains useful as an exercise to see if there are even course credit remediation differences when accounting for basic covariates. All of the results are generated using Stata 15.

Results

The review of the results is intended to provide a comprehensive overview of how students remediate course failure in NC schools. I begin by broadly mapping the OCR landscape first by examining overall enrollment followed by analyses that explore increasingly deeper layers of OCR/F2F enrollment. At the school level, I examine associations between school-level OCR enrollment and school-level characteristics followed by associations between OCR assignment and student covariates. I end with a descriptive analysis of whether OCR courses are associated with earning course credit compared to F2F courses, making connections between OCR assignment and outcomes.

Prevalence of OCR and F2F Enrollment

Failing courses required for high school graduation remains quite common with about one in five high school students in NC failing at least one core, required course between 2013 and 2016. Students in this sample failed 649,095 core courses. Out of all of the failed courses, 37.69% of the student-course records indicate that the course was neither repeated nor taken through OCR. 19.25% of course failures were later addressed through OCR exclusively, and almost double that percentage (37.79%) were exclusively F2F. 5.27% of courses were repeated F2F and OCR. Overall, F2F is the most popular option followed closely by a lack of any form of course credit remediation.[5]

Enrollment Changes Over Time and Across Schools

To assess within-school changes in OCR enrollment, Figure 1 shows the changes over time (i.e., between 2016 and 2013), within-school, in the percentage of student-course records associated with a failure that were later redeemed through OCR. This measure ranges from -100 to 100 percentage point changes with each bar on Figure 1 representing one high school sorted by percentage point change. 64% of high schools increased the percentage of student-course failures that result in OCR over time, and 29% decreased their use of OCR over time.

In order to assess the differences across schools in how students address course failure, I created a measure of OCR enrollment that represents the ratio of the number of student-course records that are associated with OCR over the number of student-course records that are associated with F2F calculated at the school-level. Figure 2 includes bar graphs of the resulting ratios by year of first failure, each 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 OCR, to 35, indicating there are 35 OCR student-course records for every one F2F student-course record at that school.

With each subsequent year, the proportion of schools with ratios of OCR to F2F above one grows from 0.16 for courses failed in 2013, 0.18 for courses failed in 2014, 0.21 for courses failed in 2015, and 0.30 for courses failed in 2016. This is shown visually by the point at which the ratio switches from less than one to greater than one shifting left over time with a higher density of schools having ratios above one. The mean ratio of OCR to F2F was at 1.04 for courses failed in 2016 from a mean of 0.64 for courses failed in 2013. Indeed, OCR became an increasingly popular option across many schools over time.

School-Level Correlates with School-Level OCR Enrollment

The results from a regression model indicating the correlations between school-level enrollment in OCR (i.e., the percent of failed courses retaken through OCR) and school-level covariates are in Table 1. Across the models, OCR enrollment is predicted to increase each year with an average of about an 8 percentage point increase in OCR enrollment each year (p<0.001 in columns (1)-(4)). In column (5), the model included the percent F2F variable, representing the percent of failed courses taken F2F. The coefficient on this variable indicates a percentage point increase in F2F enrollment is associated with almost half a percentage point decrease on OCR enrollment ($p<0.001$). Adding in Percent F2F also leads to the coefficient on school year to increase to 12 ($p<0.001$).

Few of the school characteristics have significant correlations with school-level OCR enrollment as shown in Table 1, column (1). Those variables that have significant coefficients consistently retain significance and magnitude across models (see columns (1), (4), and (5)) indicating that rural schools have higher OCR enrollment by about 4 percentage points ($p=0.003$ in column (5)), OCR enrollment decreases 0.11 percentage points for every 1 percentage point increase in enrollment of Black students ($p<0.001$ in column (5)), and OCR enrollment increases about 0.3 percentage points for every 100 student increase in enrollment ($p<0.001$ in column (5)).

As shown in columns (2) and (3), several of the contextual exposure and protective factors are associated with school-level OCR enrollment. Among contextual exposure factors, increases in the lagged chronic absenteeism rate is consistently associated with OCR enrollment such that every percentage point increase in chronic absenteeism from the previous year is associated with a 0.3 percentage point increase in OCR enrollment ($p<0.001$ in column (5)).

Among protective factors, lagged EOC proficiency rates, lagged high school graduation rates, and alternative school status are significantly associated with OCR enrollment. Test score proficiency has a negative association, with every one point increase in the previous year's EOC proficiency rate associated with a 0.2 percentage point decrease in OCR enrollment ($p<0.001$ in column (5)). However, the lagged high school graduation rate has a positive association with OCR enrollment such that every percentage point increase in the previous year's high school graduation rate is associated with 0.25 percentage point increase in OCR enrollment (p<0.001 in column (5)). In columns (3) and (4), being an alternative school is associated with 7-16 percentage point increase in OCR enrollment (p<0.001 in column (4), p=0.019 in column (5)).

Student-Level Correlates of Enrollment in OCR

The next set of results answers the fourth research question: whether student characteristics predict the likelihood of enrolling in OCR. The student and course-level coefficients from the multilevel linear probability model predicting OCR enrollment are shown in Figure 3 (full results available on request).[6] The outcome is a student-course failure that results in taking an OCR course with the comparison being student-course failure that results in F2F. Student-course failures that do not result in F2F or OCR are excluded as well as student-course failures that result in students enrolling in both F2F and OCR.

Figure 3 includes coefficients with 95% confidence intervals with a vertical line at 0. The coefficients from the linear probability model are multiplied by 100 in Figure 3 and in this discussion to ease interpretation of changes in probability. The probability of enrolling in OCR is predicted to increase over time (8.2, p<0.001). Compared to students who first failed the course in 2013, students who failed the course in 2016 would be about 25 percentage points more likely to enroll in OCR over F2F courses. The subject of the course has similarly significant and substantively large coefficients. Students are less likely to enroll in OCR if they are in math (-7.2, p<0.001) or science (-2.5, p<0.001) courses and more likely to enroll in social studies (3.6, p<0.001) courses compared to failed English courses.

Schools could be responding to certain predisposing or protective factors when enrolling students in OCR. In particular, Black students are 2 percentage points more likely to enroll in OCR (p<0.001) and students of other racial identities less likely to enroll in OCR (-1.1, p=0.014) compared to White students. Students with IEPs (-1.6, $p<0.001$), ED (-3.3, $p<0.001$), LEP (-2.4, $p=0.001$), gifted (-3.0, $p<0.001$), and overage students (-1.5, $p<0.001$) are less likely to enroll in OCR than students without these particular identifiers. Giving some credence to the explanation that OCR is a better fit for students with the predisposing factor of inconsistent attendance, the likelihood of enrolling in OCR increases as absence rates increase (0.13, $p<0.001$) such that every 10 percentage point increase in absence rates is associated with an increased probability of enrolling in OCR of 1 percentage point. This coefficient though is very small, suggesting difference in absence rates must be at a very high magnitude to make a practical difference. Other predisposing and protective factors' coefficients were not statistically significant including being Hispanic, previous LEP, 8th grade test scores, and being female.

Associations Between Remediation Options and Earning Lost Course Credit

To address whether F2F or OCR is descriptively associated with earning credit for a failed course, Table 2 includes the results from a multilevel linear probability model predicting whether course credit was earned after failing a course. The reference group is courses that a student only does F2F. The probability of earning credit through an OCR course exclusively is 12 percentage points higher ($p<0.001$) than the probability of earning credit for a student who repeats F2F only. Students who do not take OCR or F2F have much lower probability of earning course credit: 58 percentage points lower ($p<0.001$). Students who repeat a course F2F and take the course through OCR have a slightly lower probability of earning course credit (-4.3, $p<0.001$) compared to students who only repeat a course F2F.

The interactions between OCR and 8th grade test scores, student race, and IEP status are statistically significant while ED and LEP are not significant, see Table 2, columns (2)-(8). These significant interaction terms indicate students have a differential likelihood of receiving course credit for an OCR course based on prior achievement, racial identity, and IEP status. For 8^{th} grade test scores (Table 2, column (2)), the coefficient on 8^{th} grade test scores is positive (0.040, $p<0.001$), indicating students with higher test scores are more likely to earn course credit, while the interaction between OCR and test scores is negative (-0.028, $p<0.001$). I further investigate these relationships through predicted probabilities of earning course credit across the typical range of values of 8^{th} grade test scores in standardized units. As is shown in Figure 4, the likelihood of earning course credit increases for OCR and F2F courses across the typical range of 8^{th} grade test scores. However, as was indicated by the negative interaction between test scores and OCR, this relationship is attenuated for OCR students. OCR students with test scores two standard deviations below the mean have an 81 percent likelihood of earning course credit ($p<0.001$) compared to 86 percent for OCR students' test scores two standard deviations above the mean ($p<0.001$), a difference of 5 percentage points. The corresponding probabilities for F2F students are 65 percent ($p<0.001$) and 81 percent ($p<0.001$), a 16 percentage point difference.

The other significant interactions are with binary variables, easing interpretation of the interaction terms. In this discussion, I similarly multiply the coefficients in the linear probability model results in Table 2 by 100 in this discussion to ease interpretation. For Black students (Table 2, column (3)), taking an OCR course is associated with a 1.8 percentage point increase ($p=0.019$) in the likelihood of earning course credit over the 11 percentage point increase ($p<0.001$) in the probability non-Black OCR students earn course credit. Enrolling in OCR for Hispanic students is associated with a 1.6 percentage point lower probability ($p=0.033$) under the 12.1 percentage point increase ($p<0.001$) for non-Hispanic OCR students. Students with IEPs are more likely to earn course credit in OCR (1.6, $p=0.001$) than students with IEPs in F2F courses (-1.7, $p<0.001$). Given the almost identical magnitude of the coefficients on *IEP* and *IEP X OCR*, taking an OCR course effectively cancels out the negative association between having an IEP and gaining course credit. The significant interactions with these binary variables are no longer significant once all interactions are in the same model, indicating these results are potentially sensitive to the comparison group or specification choices.

Comparing the results on OCR selection and earning course credit, Black students are more likely to be assigned to OCR and more likely to earn credit while Hispanic students are not more likely to be assigned and are less likely to earn credit. ED and LEP students are both less likely to be assigned to OCR and are not more likely to earn credit through OCR. These associations indicate that student assignment to OCR might be strategic in that students who are observed to be more likely to earn credit might be assigned to those courses more whereas students who do not appear to benefit from OCR are not assigned to OCR. However, this explanation is undermined by the associations for students with IEPs who are less likely to be assigned to OCR but more likely to earn credit. Other explanations are explored in the conclusion.

Conclusion

This paper confirms speculations on the part of the media that OCR courses are becoming an increasingly popular tool that schools are using. Schools could be increasing OCR enrollment since they are observing OCR enrollment is associated with a higher likelihood of earning course credit. However, the results presented in this paper are not causal; there are many reasons why OCR students might have higher rates of gaining course credit including selecting students for OCR with a high likelihood of gaining course credit. In interviews with district officials in NC, several officials confirmed that they are more likely to enroll a student in OCR 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). At the same time, there are reasons to believe OCR enrollment would be more likely to result in course credit including students only repeating material they did not master previously, allowing the courses to be completed more quickly (Darling-Aduana 2019). OCR students having a higher likelihood of earning course credit than F2F students could indicate that the courses better fit the needs of students who failed courses, students more likely to earn course credit being assigned to OCR, or OCR courses lacking the rigor of F2F courses. Popular accounts of OCR focus on the courses being easy, gameable (e.g., googling answers), and short (e.g., Smiley 2017), but student assignment might also play a role in the higher likelihood of OCR students earning credit.

How Schools Assign Students to OCR

The correlation between school-level OCR enrollment and school covariates potentially confirms the speculated motivations behind OCR assignment in schools. Since OCR enrollment was correlated with increasing graduation rates and decreasing test score proficiency rates, schools could be making a purposeful choice to focus on high school graduation rates over test scores. This decision to increase enrollment in OCR to increase graduation rates might be logical in schools with increasing chronic absenteeism rates, especially since OCR might be particularly well suited for chronically absent students. The correlation between OCR enrollment and alternative schools adds some indication of potential generalizability of trends noted in reporting from Florida that found traditional high schools in one county would transfer students to alternative schools that relied on OCR as the primary instructional mode (Curcio 2016). In addition, rural schools might have higher enrollment in OCR because it would allow students to make up credits from home for those with transportation challenges. Schools with higher enrollments might have higher OCR enrollment because of the easy scalability of the platform, allowing the schools to assign students to OCR instead of increase the number of students in traditional courses.

Compared to F2F students, OCR students have higher absence rates and are more likely to be Black. At the same time, OCR students have fewer contextual risk factors including being less likely to be have an IEP or qualify as ED. This finding stands in contrast with the analysis suggesting OCR students are more likely to earn course credit than F2F students. OCR students seem to defy expectations since earning course credit is only weakly related to prior test scores for OCR students. At the same time, Black students have both an increased likelihood of OCR assignment and earning credit in an OCR course compared to Hispanic students who are less likely to earn credit and ED and LEP students not having differential credit earning rates. These findings supports the hypothesis that schools strategically assign students to OCR who they observe to be more successful in these courses. This relationship might not hold for students with IEPs since their accommodations might make it difficult to systematically assign them to OCR courses.

Implications for Schools

As OCR grows in popularity, it will be important to critically examine who is given access to OCR courses and why these decisions are being made. It is possible schools are responding to the presumed increased credit earning of OCR students by increasing their OCR enrollments, but this decision could have unintended consequences if OCR courses are low-quality or detract from the learning environment or rigor of the school. Schools might discover that the productivity of OCR 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 OCR. In addition, there are also many reasons to believe that students who typically fail courses might be particularly ill suited to take online courses for many reasons including low literacy levels, less exposure to complicated technology platforms, and stronger need for high-quality, in-person instruction (Viano 2018). The results point to the potential tradeoff that schools are making in increasing OCR enrollment – with schools with higher OCR enrollment also having higher graduation rates but lower test score proficiency rates..

Avenues for Future Research

This research points to many potential possibilities for future research into OCR. While OCR appears to be successful in obtaining course credit for failed courses, future research could investigate (1) if, qualitatively, school officials are observing this on the ground and then responding by increasing enrollments and (2) causally identifying if this is the case. We know little about how OCR is being implemented, how students experience the courses, and how students are enrolled in OCR; all questions that could be better understood through qualitative research. These studies could also investigate the extent to which OCR is a protective factor and/or a quick fix in addition to the role of protective factors in the school and their interaction with OCR course assignment/quality. In addition, more research using causal identification strategies can help to understand whether OCR courses do lead to better or worse student outcomes both proximally (e.g., earning course credit) and distally (e.g., graduating from high school).

Regardless of the paradigm, the effects of OCR might significantly vary based on how OCR courses are administered and the quality of the content. Schools make a variety of decisions about how to administer OCR courses ranging from requiring a certified teacher as a monitor while students take the OCR course during the school day to giving students login information and expecting students to complete the course at home without support. Schools also have many different options for OCR course providers, and different vendors might offer varying quality of courses. Examining differential effects for various course administration options and course providers is a key area for future OCR research. Hopefully these future research studies can help to inform OCR enrollment.

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Notes

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[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 https://www.dpi.nc.gov/districts-schools/high-school-graduation-requirements for more information.

[2] Most of the student-course records that are excluded are for courses with initial failures in 2017 (65.7% of dropped observations). Since 2017 is the last year of data, data are not available to follow these students a full year after course failure.

[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 2% of the sample attends more than one high school, a small enough proportion where a multiple membership model is not necessary.

[4] Even though the outcome is binary, the model is not a logistic regression model to ease interpretation of the findings. Results fit with logistic regression are qualitatively very similar and are available by request. In addition, the outcome does not include assignment to both OCR and F2F or neither option because the multilevel, multinomial logistic regression models, where the four different assignment options are all included as separate levels, would not converge.

[5] The most obvious reason why over a third of failed student-course records are not taken through OCR or repeated for credit is that these records represent students who are not on track to graduate and/or dropped out of high school. Another potential explanation for why over a third of student-course failures are not addressed through OCR or F2F lies in the requirements for graduating from high school in NC. 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 42 percent of the student-course failures that are not addressed are math courses. These students could have elected to take a different Math class that also counts toward high school graduation instead of repeating the course or taking OCR (although this might require the student to change their track from college-bound to career-ready). Giving students more time to make up courses does not substantially change these numbers. For instance, when restricted to students who first failed in 2014 and

allowing them retakes through 2017, 34 percent of courses are not taken through OCR or F2F, 20 percent through OCR and 39 percent through F2F.

[6] The ICCs from the baseline model are 0.32 at the school-level, and 0.56 at the student-within-school level, indicating that using a multilevel model is worthwhile.

Figure Titles and Notes

Figure 1: Percentage Point Change in Enrollment of Students in OCR Within School Over Time

Note. The values are calculated by subtracting percent OCR enrollment of courses failed in 2016 (allowing for OCR enrollment in 2016 or 2017) from percent OCR enrollment of courses failed in the 2013 (allowing for OCR enrollment in 2013 or 2014).

Figure 2: Ratio of OCR to F2F Courses By School Over Time By Year of Failure

Note: A small number of schools (n=7 over all years) are not shown because they exhibit extreme values on the OCR:F2F ratio. Year indicates the year the course was failed, giving students that year and the following year to take the course F2F or OCR.

Figure 3: Coefficients from the Multilevel Linear Probability Model Predicting Enrollment in OCR over F2F at the Student-Course Level with 95% Confidence Intervals

Note. The vertical gray line represents a null effect of 0. Plot excludes school-level covariates. Full results available by request. To ease interpretation, the coefficients have been multiplied by 100 to represent percentage point changes as opposed to changes in probability rate.

Figure 4: Predicted Probability of Earning Course Credit by 8th Grade Test Scores and Whether the Course Was Taken Through OCR or F2F With 95% Confidence Intervals

Tables

Table 1

Results from Ordinary Least Squares Regression Predicting Percent of Previously Failed Courses Taken through OCR by Year

	(1)	(2)	(3)	(4)	(5)
School Year	7.64***	7.97***	7.56***	7.65***	12.15***
	(0.39)	(0.37)	(0.40)	(0.44)	(0.48)
Percent F2F					-0.43***
					(0.03)
School Characteristics:					
City	3.18			2.18	1.99
	(2.36)			(2.22)	(1.57)
Town	4.61			2.87	2.45
	(2.75)			(2.51)	(1.80)
Rural	3.65*			4.20*	3.65**
	(1.80)			(1.75)	(1.24)
Percent LEP	0.13			-0.42	-0.37
	(0.32)			(0.29)	(0.24)
Percent Gifted	-0.14			0.04	0.08
	(0.08)			(0.08)	(0.06)
Percent SPED	0.18			-0.11	-0.18
	(0.12)			(0.12)	(0.10)
Percent Economically Disadvantaged	0.07			-0.07	-0.09*
	(0.04)			(0.04)	(0.03)
Percent Black	-0.11**			-0.12***	-0.12***
	(0.03)			(0.03)	(0.02)
Percent Hispanic	-0.05			0.16	0.09
	(0.11)			(0.10)	(0.08)
Enrollment (in 100s)	0.29*			0.50***	0.38***
	(0.11)			(0.10)	(0.08)
Contextual Exposure:					
% Teachers with 3 or Fewer Years of		-0.14**		-0.08	-0.10*
		(0.05)		(0.05)	(0.04)

Experience					
Number of Violent Acts		-0.01		-0.01	-0.05
per 1K Students		(0.04)		(0.04)	(0.04)
Short Term Suspension		-0.01		-0.02	-0.02
Rate		(0.02)		(0.02)	(0.01)
Percent Chronic		0.39***		0.23***	0.34***
Absenteeism, Lagged		(0.07)		(0.07)	(0.05)
Course Failure Rate, Lagged		0.14		0.10	0.14
		(0.09)		(0.10)	(0.08)
Protective Factors:					
School Per Pupil			-0.01	0.03	0.03
Expenditures (in 100s)			(0.02)	(0.02)	(0.01)
Percentage of Teachers			0.003	-0.07	-0.05
with National Board			(0.07)	(0.06)	(0.06)
Certification					
EOC Proficiency Rate,			-0.18***	-0.24***	-0.33***
Lagged			(0.04)	(0.06)	(0.04)
HS Graduation Rate,			0.25***	0.28***	0.22***
Lagged			(0.06)	(0.06)	(0.05)
Magnet School			3.37	4.76	3.68*
			(2.51)	(2.45)	(1.72)
Alternative School			15.82***	13.24***	6.80*
			(3.48)	(3.65)	(2.89)
Observations	1942	1942	1942	1942	1942

NOTE – Standard errors in parentheses; Standard errors clustered at school level. Constant omitted for brevity.

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

Table 2

Results from a Multilevel Linear Probability Model Predicting Earning Credit for a Previously Failed Course

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fixed Effects								
OCR Only	0.12^{***}	0.10^{***}	0.11^{***}	0.12^{***}	0.11^{***}	0.12^{***}	0.12^{***}	0.11^{***}
	(0.0076)	(0.0076)	(0.0081)	(0.0074)	(0.0077)	(0.0087)	(0.0075)	(0.0093)
No OCR, No F2F	-0.58^{***}	-0.58^{***}	-0.58^{***}	-0.58^{***}	-0.58^{***}	-0.58^{***}	-0.58^{***}	-0.58^{***}
	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)
OCR and F2F	-0.043^{***}	-0.045^{***}	-0.043^{***}	-0.043^{***}	-0.043^{***}	-0.043^{***}	-0.043^{***}	-0.044^{***}
	(0.0054)	(0.0055)	(0.0054)	(0.0054)	(0.0054)	(0.0055)	(0.0055)	(0.0055)
Moderators								
8^{th} Grade Test Scores		0.040^{***}						0.040^{***}
		(0.0015)						(0.0015)
8^{th} Grade Test Scores X OCR		-0.028^{***}						-0.028^{***}
		(0.0033)						(0.0029)
Black			0.027^{***}					0.030^{***}
			(0.0029)					(0.0030)
Black X OCR			0.018^{*}					0.0060
			(0.0075)					(0.0084)
Hispanic				0.0074^{*}				0.0067
				(0.0035)				(0.0036)
Hispanic X OCR				-0.016^{*}				-0.014
				(0.0074)				(0.0085)

IEP					-0.017***			-0.016***
					(0.0024)			(0.0025)
IEP X OCR					0.016***			0.0094
					(0.0047)			(0.0048)
ED						-0.053***		-0.050***
						(0.0027)		(0.0026)
ED X OCR						-0.00052		-0.010
						(0.0068)		(0.0061)
LEP							-0.0087	-0.0082
							(0.0051)	(0.0051)
LEP X OCR							0.0050	0.0039
							(0.012)	(0.011)
N	414414	414414	414414	414414	414414	414414	414414	414414
Random Effects								
Between-School Variance	0.0033***	0.0033***	0.0033***	0.0033***	0.0033***	0.0033***	0.0033***	0.0033***
(intercept)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Between-Student Variance	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
(intercept)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Residual ICC								
School level	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.023
	(0.0034)	(0.0033)	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0033)
Student-Within-School level	0.23	0.23	0.23	0.23	0.23	0.23	0.23	0.23
	(0.0042)	(0.0041)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0041)

NOTE – Student-level and school-level covariates and constant omitted for brevity but are available by request. Standard errors in parentheses. Standard errors clustered at the school level.
* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$