Postsecondary Opportunities for the Underprepared: Effects of Remediation on Educational and Labor Market Outcomes

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Recent estimates suggest that between 40% and 60% of all first-year students arrive at college unprepared and require some form of remediation (Bettinger & Long, 2009; Long & Boatman, 2013; Scott-Clayton & Rodriguez, 2012). As such, college remediation has become the center of policy debates across the country in recent years. As a growing number of states are faced with shrinking education budgets, some have begun to question the return on investment for remedial education. Some estimate that college remediation costs states and students more than $3 billion annually (Alliance for Excellent Education, 2011); while others have argued that remediation at community colleges alone costs $4 billion (Scott-Clayton & Rodriguez, 2012). Indirect costs in the form of foregone earnings for students who do not persist to graduation are similarly significant (Alliance for Excellent Education, 2011). States' responses to these fiscal concerns include restrictions on remedial course offerings, decreased funding for remedial education, and limits on which institutions can provide remediation (Long & Boatman, 2013). In some cases, enrollment caps have been imposed for remedial courses, along with restrictions on the number of opportunities students have to successfully complete them.

Adding to the pressure on legislators to amend remedial education policies is the recent implementation of the Common Core State Standards that delineate between students who are college-ready and their less-equipped counterparts (Mangan, 2014). As these standards are operationalized, we may see a substantial increase in the number of students deemed unprepared for college. A subsequent increase in demand for remediation could pose fiscal and political challenges. Thus, there is an incentive to make remediation optional, lower standards for entrance into traditional college courses, or pursue other measures that will protect states from the costs associated with remediation (Mangan, 2014).

Often the political debate centers on the way in which remediation seemingly costs the public twice, because the skills that students learn in remediation should have been gained prior to college (Boylan, Bonham, & White, 1999; Crisp & Delgado, 2014). Much of the controversy also focuses on the effect developmental education has on students. While these programs may serve as a means of fostering student access and degree completion (e.g., Lavin & Weininger, 1998; McCabe, 2000; Parker, 2007), critics of developmental education point to research that reveals possible negative academic, financial, and psychological effects of the courses (e.g., Bailey & Cho, 2010; Bettinger & Long, 2007). Disparities in the types of students who most often qualify for remedial programs add an additional layer of challenge to the debate.

Limiting access to remediation may not prove detrimental to students on the margins, but it may pose consequences for the least prepared students, a disproportionate number of whom are from low-income or minority backgrounds (Attewell, Lavin, Domina, & Levey, 2006; Chen, Wu, & Tasoff, 2010; Perna & Titus, 2005; Radford, Pearson, Ho, Chambers, & Ferlazzo, 2012). For these students, remedial courses may be the only avenue into college. Yet, limited resources and public support for remediation, coupled with demands for higher rates of college completion, can be a powerful disincentive for serving them (Long & Boatman, 2013; Sullivan & Nielsen, 2013).

At the same time we see pressures to decrease support for remediation, recent research suggests that students have less social mobility than in previous generations. For example, relative to previous generations, today's students are less likely to achieve higher levels of educational attainment than their parents (Beller & Hout, 2006; Hout & Janus, 2011). This is particularly troubling as we continue to see the income (Duncan & Murnane, 2011) and achievement (Reardon, 2011) gap between high and low family incomes widen. Any policies that limit college opportunities afforded by remediation may exacerbate these inequities and limit social mobility.

Purpose and Research Questions

While policymakers have become increasingly concerned about remediation in recent years, we still know surprisingly little about the role that remedial course enrollment has on labor market outcomes, and research is inconclusive about its effects on degree attainment. With the exception of Martorell and McFarlin (2011), research has not addressed remediation and labor market outcomes. Understanding the role that college remediation has in expanding educational opportunity and increasing labor market success is important information for the current policy debate. Therefore, the purpose of this paper is to explore the effect of remedial course enrollment on labor market outcomes (earnings and employment status) and baccalaureate degree attainment.

In addition to comparing those who are remediated to those who are not, an approach adopted by previous research, we also compare those who have access to college through remediation to matched students who did not attend college. Unlike previous research that only compares those needing remediation to college peers who do not need remediation, this study is the first of its kind to examine outcomes of high school students who enroll in college through remedial classes and similar high school graduates who do not enroll in college. In this way, we are able to fully explore the implications of remediation and the role remediation plays in providing educational opportunities to underprepared students and how it affects educational outcomes. Thus, this study asks two research questions:

1. Compared to those who do not attend college, do those who enroll in college and require remediation differ in their earnings and employment status eight years after high school graduation?
2. Among college students, do those enrolling in remedial classes have different labor market and educational outcomes than those who do not?

We use the National Center for Education Statistics' Educational Longitudinal Study of 2002 (ELS:2002), a nationally representative sample of high school students, to examine the effect of enrolling in college remedial courses on labor market outcomes. We employ propensity score methods with an array of important covariates (e.g., subject specific achievement test scores) to reduce selection bias introduced by choosing or being placed into remedial coursework.

Background and Conceptual Framework

Remedial courses, which fall under the broad term of remediation, are the support used by colleges to address the academic needs of underprepared students. These courses target underprepared students with the purpose of improving their abilities to handle college-level material. Remediation is pervasive across all types of colleges and universities. Recent studies suggest that more than 50% of college-going students participate in remedial education (Kirst & Reeves Bracco, 2004; Scott-Clayton and Rodriguez, 2012). Others suggest that the overwhelming majority of public high school graduates (68%) are not academically qualified to attend a four-year college (Greene & Forster, 2003).

In fall 2000, more than three-quarters of all undergraduate-serving institutions offered some type of remedial education (NCES, 2003). Mathematics remediation appears to be the most pervasive. Some estimates indicate that 90% of two-year institutions and 80% of four-year institutions offer some math remediation to their students (Lesik, 2006).

Inequities in the Need for College Remediation

While remediation is ubiquitous in US Higher Education, it seems that traditionally underrepresented groups are more likely to need college remediation than their peers. First-generation, low-income, and minority students are disproportionately represented (Sullivan & Nielsen, 2013). Several studies find that African American and Latino students are more likely than White and Asian American students to require remediation (Bettinger & Long, 2005; Crisp & Delgado, 2014; Crisp & Nora, 2010; Greene & Forster, 2003; Radford et al., 2012).

Likewise, there is an income gap in the need for remediation. Students from low income families are significantly more likely to require college remediation than their wealthier peers (Chen, 2005; Crisp & Delgado, 2014; Nuñez & Cuccaro-Alamin, 1998; Radford et al., 2012). Many point to inequities in high school contexts as an explanation for these disparities (Attewell, Heil, & Reisel, 2011; Howell, 2011; Niu & Tienda, 2013). High school socioeconomic composition and social class emerge as positive predictors of students' college aspirations (Bain & Anderson, 1974) and knowledge (Bell, Rowan-Kenyon, & Perna, 2009), enrollment (Alexander & Eckland, 1977; Engberg & Wolniak, 2010; Perna & Titus, 2005), expectations (Frost, 2007), preparation (Perna, 2005), and persistence (Johnson, 2008). Whatever the causes, it seems that college remediation is a pathway to college and the earnings premium associated with college attendance.

Outcomes of College Remediation

The research on outcomes associated with remediation are nuanced at best and are greatly influenced by students' background characteristics and pre-college educational experiences

(Long & Boatman, 2013). The problem with much of the literature associated with the effects of remediation is that many do not attend to selection bias and simply compare remedial students to those who did not need remediation. Those who need college remediation are likely to be substantively different from those not requiring remediation on a host factors that likely could influence both the need for remediation and college outcomes.

In recent years, several studies have employed quasi-experimental techniques to account for selection bias associated with remediation. Because remedial courses placement invariably relies on a test cut score, many studies employ regression discontinuity (RD; see for example, Boatman & Long, 2010; Calcagno & Long, 2008; Lesik, 2006; Martorell & McFarlin, 2011; Moss & Yeaton, 2013; Scott-Clayton & Rodriguez, 2012). The studies have found mixed results for the effects of college remediation.

For example, one such study (Calcagno & Long, 2008) of Florida community college students, found remediation did not affect persistence, associate's degree attainment, or successful transfer to a four-year institution. Another found that remedial courses had a negative effect on one-year persistence, but little or no effect on degree completion for those near the placement test score cutoff (Martorell & McFarlin, 2011). Similarly, Scott-Clayton and Rodriguez (2012) found that remediation did not significantly affect a range of outcomes, including persistence, degree completion, academic performance in college courses post-remediation, and college exit exam scores. In contrast, Boatman and Long (2010) found that among students near the math placement cutpoint, those requiring remediation were less likely to earn a degree or certificate. In general, they also found negative effects of reading and writing remediation on outcomes.

While the use of RD results in high internal validity, these studies nonetheless have their limitations, namely they are limited in their external validity. All are limited to single states or institutions, limiting their generalizability beyond those contexts. In addition, these studies look only at students near the cutpoint and typically are unable to look at the least prepared students, which are most likely those who come from disadvantaged families.

One other notable study (Attewell et al., 2006) analyzes a nationally representative dataset (National Educational Longitudinal Study 1988) using propensity score matching (PSM) to reduce the effect of selection bias. This study found that remedial students at two-year colleges were no less likely than non-remedial students to earn an associates degree or certificate. They did find that students at four-year colleges who required remediation were 6% to 7% less likely to earn a baccalaureate degree than those who did not need remediation.

What few of these studies address is the notion that remediation may be a path to increased earnings for students who may not have had access to college otherwise. One study (Martorell & McFarlin, 2011) did examine earnings, along with a series of other educational outcomes. They found that students requiring remediation earnings were not statistically significantly different than college students who did not require remediation. As with the other studies that employ RD, these findings have high internal validity; however, examining students only near the placement test cutpoint and studying college students in one state limit the external validity. Furthermore, this study overlooks the notion that access to college through remediation may have an effect when comparing these students to similar students who did not attend college.

Conceptual Framework

This study of college remediation is framed by theories of human, social, and cultural capital. At the core of the framework is human capital theory. Human capital theory suggests that individuals accumulate productive capacities (e.g., knowledge, skills) through investments in education, which can be exchanged for increased earnings, power, and status (Becker, 1993). Students decide to enroll in college by comparing expected benefits (monetary and non-monetary) with expected costs (costs of attendance and foregone earnings). Human capital theory suggests that capital can be accrued through any investments in education, even remediation alone.

Students also weigh these costs and benefits of college in the context of their preparation. Yet, while preparation is cited as an essential component of improved college access (Attewell et al., 2006; Perna, 2005), less is known about *how* students acquire the skills and knowledge necessary to succeed in college. Extant literature on college access and success provides some insight into this question by exploring the role of human, social, and cultural capital. In general, these factors are associated with academic preparation (e.g., Perna, 2006), academic achievement (e.g., Wolniak & Engberg, 2010), and college enrollment (e.g., Engberg & Allen, 2011).

Sociologists also argue that decisions about educational investments are made within unique social contexts, which are often closely related to their socio-economic backgrounds. Habitus reflects the enduring beliefs, attitudes, perceptions, and values acquired from the immediate environment (Bordieu & Passerson, 1977; McDonough, 1997) that define and delimit educational alternatives. One's habitus reflects their demographic characteristics (e.g., race/ethnicity, SES) and accumulated social and cultural capital (Perna, 2006). Researchers often define social capital as an individual's access to information and support acquired through interactions with those in their social networks (Coleman, 1988). Cultural capital is described as an individual's cultural knowledge, language skills, and credentials, derived largely from parents' class status (Bordieu & Passerson, 1977).

In addition to forms of capital, this study is guided by the literature on social mobility. Scholars of social mobility have argued that growth and openness in educational systems are keys to intergenerational mobility (Blau & Duncan, 1967). Growth in education enhances mobility by increasing the number of opportunities to enroll. Openness fosters mobility by removing barriers for students from low socioeconomic backgrounds. Remediation serves as a way to provide access (openness) to higher education for underprepared students, who disproportionately come from underrepresented backgrounds and who otherwise may not have the opportunity to attend college.

Guided by the concepts of social mobility and openness, this paper seeks to understand the opportunity remediation affords underprepared students by exploring how students enrolled in remedial classes differ from two distinct groups. For our first comparison group, we argue that remediation serves as an intervention that provides access to higher education and subsequently affects labor market outcomes. For this group, we compared students who access college through remediation to high school graduates did not attend college. In this set of analyses, we view any things that occur after access to college through remediation (or not) as downstream outcomes (e.g., degree attainment). This approach allows us to capture a broader picture of how providing opportunities to low-income students influences mobility. Our second approach is more traditional in that we compare those who enroll in remedial courses to those who attend college but do not require remediation. This, too, offers an important snapshot of how remediation affects educational outcomes and examines the opportunities it gives underprepared students.

Methods

This study uses the ELS:2002, which follows a nationally representative sample of tenth graders in 2002 through high school and postsecondary education and into the workforce. The initial survey and first follow-up provide rich pre-college data on student background, student achievement, and high school context. The third follow-up provides information on an array of college variables, including college attendance, college remediation, and postsecondary persistence and attainment rates, along with labor market experiences. To date, no other national study provides this wealth of information and allows us to follow students from high school into the labor market.

To address the issue of selection bias, which is problematic in studies of remediation, scholars have developed a counterfactual model of causal inference (Rosenbaum & Rubin, 1983). In a randomized experiment, the random assignment of subjects to control and treatment groups guarantees equivalency between groups. Thus, any differences in outcomes between treatment and control groups can be attributed to the treatment alone. The counterfactual model in quasi-experimental research is achieved by first building a model that predicts the treatment variable (remediation, in this case). A sample is then built using the propensity score, such that the treatment and control groups are equivalent on background characteristics, thus reducing selection bias.

Analytical approach

We employ inverse probability weighting, a form of propensity score analysis, to analyze the effects of remediation on the outcomes of interest. A commonly used procedure is to summarize all the variables in X with a single variable called the propensity score (Rosenbaum & Rubin, 1983). "The propensity score is the true probability of unit i receiving treatment, given the covariates X_i" (Ho, Imai, King, & Stuart, 2007, p. 218). Therefore, this study will seek to compare both individuals that are similar to the treatment group on all relevant pretreatment characteristics *X*, as determined by the probability (propensity) of participating in the treatment. Data analysis for this study will include two major design steps prior to the empirical analysis.

The first step is to estimate the probability of treatment, by calculating the propensity score for each individual using the covariates. Covariates do not need to be statistically significant to be included in the model; however the goal is that treated and control groups are balanced on the covariates, indicating that they have equivalent background characteristics. The propensity score equation is a logit model that predicts the probability of an individual receiving the remediation treatment:

$$\text{logit}(\textit{remediation} = 1) = \beta_0 + \beta_1(x_i) + \beta_2(x_i) + \ldots \beta_k(x_{ki})$$

For this model, *i* represents the value of an individual in the predictor equation. This model has one outcome variable, *remediation*, which indicates the probability of a student being remediated. All covariates will be added to the model, and the effects are represented by the β regression coefficients.

After all propensities are calculated, the second step is to calculate weights based on the inverse probabilities of the propensity scores. For this analysis, we are concerned with calculating the average treatment effect on the treated (ATET). The ATET focuses specifically on the effects of the treatment for those whom the intervention was intended (Caliendo & Kopeinig, 2008). Because this study is concerned with the ATET, the treated are not weighted, but the controls are weighted towards the treated means. The weights to estimate ATET are as follows:

$$\text{Treated units} = 1 \qquad \text{Control units} = p\,/\,(1 - p)$$

The logic behind inverse probability weighting is that some control units count more than others when conducting the analysis. Controls that do not have the remediation treatment, but are similar to the treated units on the covariates, will tend to have high propensities as well. Therefore, control units with high propensities will also be weighted more than those with lower propensities. Control units with low propensities will count less in the statistical analysis, as these units are not similar to the treated units. To be conservative, units with propensities of less than .01 or greater than .99 will be dropped from the analysis. Dropping units at the tails of the distribution will remove units with very large and low weights. This decision to trim the propensities will ensure that there is overlap between treated and untreated units in the model.

Inverse probability weighting has several advantages over traditional propensity score matching methods. One, its logic is intuitive and easy to implement, yet it achieves similar ends. Employing inverse probability weighting allows the researcher to run different analyses by simply adding the weights to the regression equation. Each empirical model will vary depending on the outcome variable, but all models will include the calculated inverse probability weights. Two, using an inverse probability weighting approach allows the research to maintain a large sample size, which results in high external validity. This is particularly important when working with nationally representative datasets that have the primary aim of broad generalizability. Other matching methods require you to trim cases that do not have common support and often reduce sample sizes dramatically. Three, inverse probability weighting provides doubly robust estimations of treatment effects. Because this analytical approach requires models to be run in a two-step procedure, we have some assurances that our estimates are correct. Unlike other modeling approaches, we have two chances to specify our model correctly.

Variables

Treatment variables. This study is focused on the effects of remediation, which is defined by students taking remedial coursework in college. Remedial courses are offered in reading, writing, and math subject areas. We examine the overall effects of taking any remediation course, as well as examining each remedial subject as a separate treatment.

Outcome variables. We use two labor market outcome variables for this study - earnings and employment – and baccalaureate degree attainment. All three dependent variables are measured eight years after high school graduation. The first outcome variable is a continuous variable that indicates an individual's annual earnings. Because those not employed for the year will have zero income and may bias our results if the remediation affects the likelihood of having zero income, we run our models two ways: excluding those with zero income and including those with zero income. The second outcome variable is a binary variable that indicates if an individual is employed or not. For this measure, we exclude those who are unemployed individuals and are not looking for work. Our final measure is a dichotomous variable indicating whether they have earned a baccalaureate degree.

Covariates. It is fundamental to select the appropriate covariates to have a strong propensity model. As Caliendo and Kopeinig (2008) explain, "It should be clear that only variables that are unaffected by participation (or the anticipation of it) should be included in the model. To ensure this, variables should either be fixed over time or measured before participation" (p. 38). Covariates are selected based on prior research findings and logical explanations for what drives treatment assignment. Covariates will be included that affect both the treatment assignment and the dependent variable (Ho et al., 2007). Therefore, variables will be selected that affect both being assigned to remedial coursework and labor market outcomes.

Covariates will be selected from five large categories of variables: demographics, habitus, human capital, social capital, and cultural capital. Appendix A includes a description descriptive statistics of the variables included in the model. All covariates are measured in high school, which is prior to participation in the remediation treatment. The first set of covariates includes student demographic information: sex, race, and socioeconomic status, a composite of family income, parental education, and parental occupation prestige. The second set of covariates captures a student's academic ability and preparation in high school that would be likely predictors of remediation. These ability/preparation covariates include high school GPA, highest math course taken in high school, and reading and math achievement test scores.

The conceptual framework guides the last sets of covariates in the propensity model. First, we include two variables that measure human capital: average number of hours spent working and average number of hours per week spent studying. We also select variables that capture a student's individual habitus, which encompasses their beliefs, attitudes, and perceptions. Students answered two questions in high school that indicate their perception of education and employment. The two variables that will be included in the habitus set are the student's highest level of education they expect to complete and the education they think they will need for their expected job at age 30. Second, we introduce variables that capture a student's level of social capital. This is a composite variable that captures how involved a student's parent is in the community and at school. Lastly, variables are selected that capture how much cultural capital a student has in high school. This composite variable represents a student's social class by indicating which resources are available from their family. The variables in the cultural capital set include having access to the newspaper, magazines, computer, internet, books, and outside entertainment (i.e. concerts, plays, movies).

Comparison groups

We utilize two different comparison groups for our analyses. Because we employ inverse probability weighting, one can conceptualize that these groups are, in essence, matched on the covariates with our treated (remediation) group.

Non-college comparison group. The first set of models compares those who did not attend college to those who did by enrolling in any remedial class. This set of models answers the first research question: *Compared to those who do not attend college, do those who enroll in college and require remediation differ in their earnings and employment status eight years after high school graduation?* We examine the overall effects of remediation on all students in the sample, as well as explore these effects by whether a student starts at four-year or two-year college. We also perform a series of subgroup analyses that focus on underrepresented minorities (African American, Hispanic, Native American, and multi-racial/ethnic) and students from low and high socioeconomic backgrounds (bottom and top quartile, respectively). We also explore how different remedial subject areas (reading, writing, and math) might effect labor market outcomes. Each subject area will be treated as a separate treatment for this group of analyses. We will examine the effects overall and then examine community college students and 4-years students separately.

It is important to note that we use this group to examine remediation as an access point or intervention given to underprepared students. If not in place, these students may not have access to higher education. We also note that we view degree attainment as a downstream outcome for this set of analyses.

College non-remediation comparison group. For our second set of analyses, we run a parallel set of models but include only students who attended college and compare students who were remediated versus college students who were not remediated. This is the common comparison group used in previous research. This set of models answer the second research question: *Among college students, do those enrolling in remedial classes have different labor market and educational outcomes than those who do not?*

Limitations

This study is limited in that it does not include some valuable information about remediation behaviors. For example, it would be helpful to know how many remedial courses a student took and how they performed in the remedial classes. It also would be instructive to know how students performed in subsequent college courses. Follow-up work will be able to explore these issues when the ELS transcript data are release later this year.

It is also important to note that we only know whether students enrolled in remediation. We know nothing about the extent to which students needed remediation and complied with their colleges' recommendations to take remedial courses. These issues may confound our findings in that some students likely do not follow the recommendations of their institution.

We also offer some caution in our reliance, in some cases, on self-reported data. For example, our study relies on student self reports of their remedial course enrollments and salary. Comparing averages of the data to national averages suggests that the self-reported information is reasonable. However, given the relative sensitivity of some of the questions, it is quite possible that bias is introduced through misreports.

As with any national study of treatment effects that relies on secondary data, we know little about the specifics of each campus' treatment. It is possible that some campuses are quite successful in remediating students, while others struggle preparing their underprepared students to do college work. For our models that compare remediation students to other college students, this could explain the lack of a remediation effect. We recognize that there are campuses where remediated students do poorly and non-remediated students outperform them. Our findings simply suggest that, on average, students do not appear to be penalized for enrolling in remedial courses.

Finally, while we believe our matching model is quite comprehensive in including variables that affect selection into the treatment group and our outcome variables, some important unobservables may remain. We, therefore, offer some caution in the interpretation of our findings. However, given that we cannot randomly assign people to remedial education, we believe our approach is reasonable. We also believe the external validity of our approach extends previous single institution quasi-experimental studies that have high internal validity, but limited external validity.

Results

We run a series of models that explore labor market outcomes eight years after graduating high school. Our first series of models explores the effects of remediation relative to high school graduates who have not attended college. All of our tables include coefficients from a simple bivariate model along with coefficients resulting from the two step inverse probability weighting process described above. Our earnings models use two different versions of salary: one that includes zero values and the other that excludes cases with zeroes.

The first series of models compares students who take any remedial course (math, reading, or writing) to those who never attended college to assess the effect that access to college through remediation has on outcomes. Our second set takes the more traditional approach and compares remedial students to college students who do not require any remediation. Our final set of models examines the effects of specific remedial subjects on labor market outcomes to explore whether there are differences in types of remediation required.

In addition to comparing remediated students to two different groups, we also test the heterogeneity of remediation effects by running models for different subgroups. Our models examine the type of college students attend, along with individual characteristics including SES and underrepresented minorities (URMs; African American, Hispanic, and Native American).

Non-college Student Comparison Group and Labor Market Outcomes

Table 1 presents how remediation affects earnings. With only one exception, high SES remediation students attending community colleges, college remediation positively affects earnings. Even when we narrow our sample to only those with salaries above zero, remediation has a positive effect.

Insert table 1 here

Relative to high school graduates who did not attend college, students accessing college through any remedial courses, on average, earn approximately between \$6,800 and \$4,800 more (all observations included and zero salaries removed, respectively). Remedial students at four-year colleges have a greater salary boost than those at community colleges. Relative to those who do not attend college, those who have access to four-year colleges through remediation earn approximately \$7,000 to \$10,000 more. At community colleges, the differential is between \$4,000 and \$2,500.

Across the different subgroups, we see similar earnings patterns with some nontrivial differences. When compared with URMs who did not attend college, the remediation premium is somewhat smaller across the different models. Among all URMs, the effect of remediation is between \$3,500 and \$5,000. At four-year institutions, the premium ranges between approximately $7,300 and $4,800. The effect is smaller at community colleges, falling between $2,100 and $3,200.

Remediation appears to provide an important earnings boost for those from low SES families (bottom quartile). The effect of remediation for those from low SES backgrounds ranges from $3,600 to $7,800. In many cases, this effect is larger than what we see among those from high SES backgrounds (top quartile). Perhaps most compelling is the effect of remediation for low-income remedial students at relatively low cost community colleges. When we restrict our sample to those from low SES families, enrolling in any remediation community college course results in a $3600 to $5000 increase in earnings. For the high SES sample, the premium ranges between $2500 and $4800.

Although the effects are a bit more modest, remediation, in general, appears to significantly positively affect employment status (see Table 2). Relative to those who did not attend college, college students who enrolled in any remedial courses were approximately 30 percentage points more likely to be employed. Likewise, community college students who enrolled in any remedial course were 36 percentage points more likely to be employed than those who did not attend college.

Insert table 2 here

The effects of remediation on the URM and low SES subgroups were similar to the overall effects. Both subgroups were approximately 30 percentage points more likely to be employed if they took any remediation while in college.

College Student Comparison Group and Labor Market Outcomes

Our next series of models compare college students who enrolled in remediation to college students who did not. Table 3 displays the effect of any remediation course on earnings.

When comparing remedial students to college students who did not enroll in remedial courses, we find convincing evidence to suggest that remediation does not affect earnings. Of the 24 models presented in Table 3 where we utilized propensity score analysis, we observed a statistically significant effect for only one model, and that result was a positive effect for the high SES subgroup.

Insert table 3 here

Similarly, we also see no evidence that remediation affects employment status (see Table 4). In other words, after we account for selection in our full models, we find no employment status penalty for remediation, regardless of subgroup or where the student attended college. There does not appear to be a deficit accrued by enrolling in remediation.

Insert table 4 about here

College Remediation and Baccalaureate Degree Attainment

Table 5 presents the results of our baccalaureate degree attainment model (eight years after high school graduation). The bivariate results likely reflect the popular sentiment that students who enroll in remediation are less likely to earn a baccalaureate degree. This holds true whether students start at a four-year institution or a community college. However, when we account for selection, the differences between remediated and non-remediated students are no longer statistically significant. It is important to note that students who start at a community college and enroll in any remedial classes are as likely as their community college peers to earn a baccalaureate degree.

Insert table 5 here

College Remediation Subject Results

Because previous research has found that remediation subjects differentially influence outcomes (see, for example, Attewell et al., 2006), we also explore how different remediation subjects affect labor market outcomes. Similar to our analyses of any remediation course enrollment, we find that enrolling in a remedial course positively affects earnings when compared to those who did not attend college. In particular, the math premium is quite large, ranging between $5,200 (salary greater than zero) and $7,100 (all observations). When we compare students who enrolled in remediation to non-remediated college students, we see few statistically significant differences in earnings.

Insert table 6 here

It also does not appear that college reading, writing, and mathematics remediation do not have differential affects on the likelihood of graduating (see table 7). Across all three subject and four-year and two-year colleges, with the exception of one positive effect (writing remediation at four year colleges), we see no affect of each of the subjects on baccalaureate degree attainment.

Insert table 7 here

Discussion and Implications

The findings of this study provide an important counter-narrative to current conversations about college remediation. We offer some important evidence to suggest that remediation may not be as harmful as many perceive. Remediation students appear to have similar labor market outcomes and likelihood of earning a baccalaureate degree as their more well-prepared college peers. Even remedial students who start at a community college are as likely as non-remedial community college students to earn a bachelor’s degree.

Perhaps more important are our findings related to social mobility and remediation. Access to college through remediation appears to have important benefits. Unlike previous research that only compares those needing remediation to college peers who do not need remediation, this study is the first of its kind to look at outcomes of students who take remedial classes and similar high school graduates who do not enroll in college. This approach highlights the opportunity provided by remedial coursework and the positive effect college remediation has on earnings and employment status.

What these findings tell us is that remediation as an intervention and gateway to college have the potential to provide upward mobility. Regardless of downstream outcomes, such as degree attainment, underprepared student labor market outcomes are improved by going to college by taking remedial courses, than not going to college at all. Consider that approximately 40% of those who went to college in our study completed a baccalaureate degree (63% for those who started at a four-year college and 20% for those who started at a community college). If remediation does not hurt one’s chances to complete a degree, but improves labor market outcomes, it seems that college remediation serves a broader social good.

This also suggests we could increase college opportunity and social mobility by encouraging more relatively underprepared students to access college through remedial coursework. Outreach efforts that communicate to students the techniques provided to get them college-ready may expand access to college. In addition, many four-year campuses hide the fact that they offer remedial coursework. It seems that open enrollment institutions may reframe these efforts an provide information to prospective students about ways they assist in getting them prepared to do college work. Keep in mind we are not encouraging an expansion of remediation to include students who are ready for college work. Our findings simply suggest that it may be wise for colleges to reach out to students who may be underprepared but can prove they will benefit from remediation.

Our findings around math remediation seem particularly important given that so many students come to college unprepared for college-level math. We find that gaining basic math skills through remedial coursework translates into higher earnings. At the same time, math remediation does not affect degree attainment or employment status. Perhaps concerns about concerns associated with having the high number of students in remedial math are misplaced.

This paper also raises important questions about the purposes of remedial coursework and college. While we would not argue that degree attainment should have less importance in policy discussions, but we do posit that college remediation is an important investment in human capital regardless of whether remediated students complete a degree. Taken another way, one of the primary purposes of college attendance is to earn a degree. However, many would also argue that simply educating students and giving them basic skills to better position themselves in the workforce is also important. As fiscal concerns over remediation are discussed, perhaps these findings would suggest that investing in remedial education has public benefits to society. Students seem to be benefiting personally from enrolling in postsecondary education through remediation, and their productivity in the labor market would likely result in greater economic benefits to society.

Others have argued that the skills students acquire in remedial coursework should have been learned prior to college. Some suggest that remediation essentially costs the public twice, as students are repeating coursework and concepts that they should have learned in high school. While this argument may have merit, this study provides evidence to suggest that the investment in remediation may be worth it. Ensuring that students have basic skills and abilities appears to payoff. Our study suggests policymakers should encourage colleges and universities to make remedial education can be more accessible to students in high school.

All this is not to say that remediation is not without its costs. Although students can use federal financial aid to cover remedial courses, many have to pay for them out of pocket. In addition, students have a maximum Pell Grant amount that can become problematic if students need to take multiple remedial courses. These costs, in addition to time spent not working, present real challenges for students. Given the benefits we see here, perhaps policymakers can explore how we fund these courses. Current efforts to accelerate remedial courses and to provide better placement appear to hold some promise in reducing student costs. Our findings suggest that policymakers and campus leaders should make investments in improving remedial education rather than limiting access to these courses.

Our findings suggest that policymakers and college officials should proceed with caution when making policies that limit access to remediation. This study suggests that offering underprepared students a way into college through remediation leads to important educational and labor market outcomes. Remediation serves an important way to provide access (openness) to higher education to those who otherwise may not have had the opportunity. We find convincing evidence that that access through remediation affects labor market outcomes and social mobility.

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Table 1. The effect of any remediation on earnings: Remediated students compared with those not attending college

	All college remediation vs. HS graduates			4-year college remediation vs. HS graduates			Community college remediation vs. HS graduates		
		Propensity score analysis			Propensity score analysis			Propensity score analysis	
	Bivariate	All observations	Salary greater than zero	Bivariate	All observations	Salary greater than zero	Bivariate	All observations	Salary greater than zero
All students									
Coefficient	9321.90 ***	6758.96 ***	4835.82 ***	12932.74 ***	9669.12 ***	6905.18 ***	4887.52 ***	3979.33 ***	2501.53 ***
SE	(512.47)	(514.76)	(602.40)	(607.86)	(685.93)	(791.4)	(576.47)	(537.56)	(642.07)
N	7614	7610	5413	5806	4903	3560	5417	5417	3663
URMs									
Coefficient	6515.81 ***	4978.82 ***	3499.48 ***	9580.73 ***	7266.13 ***	4824.55 ***	3894.50 ***	3191.12 ***	2119.60 *
SE	(742.41)	(715.31)	(854.72)	(960.74)	(968.76)	(1160.14)	(849.92)	(748.92)	(912.18)
N	2958	2958	2041	2263	1854	1275	2357	2357	1554
Low SES									
Coefficient	7238.64 ***	6001.38 ***	5073.54 ***	9120.73 ***	7388.06 ***	7848.74 ***	5405.33 ***	5000.07 ***	3592.72 ***
SE	(876.83)	(826.37)	(1029.75)	1637.07	1278.51	1633.38	(1086.90)	(812.94)	(1007.84)
N	2317	2304	1504	1840	1195	766	2004	2001	1271
High SES									
Coefficient	11458.52 ***	7913.38 ***	4421.62 **	13977.97 ***	10978.21 ***	6115.61 **	5128.18 **	4795.19 *	2477.40
SE	(1776.01)	(1413.46)	(1587.29)	1926.89	1726.62	1884.14	(1906.98)	(1878.57)	(2219.39)
N	1543	1543	1243	1186	1144	925	654	654	484

Note: ***p<.001, **p<.01, *p<.05

Unstandardized coefficient represents the premium associated with college remediation in dollars.

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

All observations includes those who have a salary of 0.

Table 2. The effect of any remediation on employment status: Remediated students compared with those not attending college

	All college remediation vs. HS graduates				4-year college remediation vs. HS graduates				Community college remediation vs. HS graduates			
	Bivariate		Propensity score analysis		Bivariate		Propensity score analysis		Bivariate		Propensity score analysis	
All students												
Coefficient	-0.698	***	-0.360	*	-0.769	***	-0.264		-0.623	***	-0.447	***
SE	(0.077)		(0.143)		(0.097)		(0.244)		(0.099)		(0.122)	
Odds ratio	0.498		0.698		0.464				0.536		0.639	
N	7614		7610		5806		4903		5417		5417	
URMs												
Coefficient	-0.66	***	-0.34	*	-0.83	***	-0.27		-0.543	***	-0.362	*
SE	(0.114)		(0.154)		(0.161)		(0.258)		(0.138)		(0.158)	
Odds ratio	0.517		0.711		0.436				0.581		0.696	
N	2958		2958		2263		1854		2357		2357	
Low SES												
Coefficient	-0.55	***	-0.34		-0.56	**	-0.34		-0.557	**	-0.440	*
SE	(0.139)		(0.198)		(0.204)		(0.197)		(0.170)		(0.202)	
Odds ratio	0.579				0.571		0.579		0.573		0.644	
N	2317		2304		1840		1195		2004		2001	
High SES												
coefficient	-1.00	***	-0.54		-1.00	***	-0.19		-0.98	**	-0.87	*
SE	(0.219)		(0.376)		(0.234)		(0.480)		(0.299)		(0.381)	
Odds ratio	0.370				0.368				0.376		0.418	
N	1543		1543		1186		1144		654		654	

Note: ***p<.001, **p<.01, *p<.05

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

Odds ratios provided when statistically significant

Table 3. The effect of any remediation on earnings: Remediated students compared with college students not needing remediation

	Remediated vs not remediated			4-year college remediated vs. not remediated			Community college remediated vs. not remediated		
		Propensity score analysis			Propensity score analysis			Propensity score analysis	
	Bivariate	All observations	Salary greater than	Bivariate	All observations	Salary greater than	Bivariate	All observations	Salary greater than
All students									
coefficient	-774.75	559.50	163.74	-831.76	1218.01	629.25	-1717.63 *	-106.27	-299.22
SE	(513.63)	(471.96)	(510.23)	(696.09)	(639.48)	(673.32)	(713.93)	(695.85)	(774.61)
N	9935	9935	8012	6280	6280	5225	3633	3633	2777
URMs									
coefficient	-898.49	-387.10	-393.43	-2435.68	623.05	-679.95	-1654.00	618.80	170.41
SE	(832.11)	(764.70)	(837.43)	(1226.03)	(1154.19)	(1223.98)	(1108.99)	(1028.67)	(1147.81)
N	2780	2780	2159	1489	1489	1208	1282	1282	948
Low SES									
coefficient	-930.08	965.46	800.45	25.63	2440.00	1602.39	-1422.24	-34.89	121.06
SE	(1096.90)	(1097.62)	(1234.59)	(1805.44)	(1717.08)	(1900.53)	(1367.43)	(1388.91)	(1559.59)
N	1576	1576	1208	687	687	537	877	877	666
High SES									
coefficient	-785.02	1132.79	523.04	742.43	2111.34 *	1660.60	-2191.24	-703.20	-1924.22
SE	(965.94)	(887.22)	(942.14)	(1128.86)	(1009.75)	(1050.35)	(1864.90)	(1821.20)	(2032.56)
N	3697	3697	3079	2933	2933	2473	762	762	605

Note: ***p<.001, **p<.01, *p<.05

Unstandardized coefficient represents the premium associated with college remediation in dollars.

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

All observations includes those who have a salary of 0.

Table 4. The effect of any remediation on unemployment: Remediated students compared with college students not remediated

	All college: remediation vs. no remediation		4-year college: remediation vs. no remediation		Community college: remediation vs. no remediation	
	Bivariate	Propensity score analysis	Bivariate	Propensity score analysis	Bivariate	Propensity score analysis
All students						
Coefficient	0.176 *	-0.009	0.225 *	0.066	0.038	-0.096
SE	(0.080)	(0.088)	(0.108)	(0.118)	(0.123)	(0.132)
Odds ratio	1.193		1.252			
N	9935	9935	6280	6280	3633	3633
URMs						
Coefficient	0.151	-0.045	0.142	-0.143	0.064	-0.043
SE	(0.132)	(0.144)	(0.196)	(0.222)	(0.183)	(0.199)
Odds ratio						
N	2780	2780	1489	1489	1282	1282
Low SES						
Coefficient	0.105	-0.023	0.008	-0.207	0.215	0.094
SE	(0.173)	(0.194)	(0.260)	(0.291)	(0.241)	(0.269)
Odds ratio						
N	1576	1576	687	687	877	877
High SES						
coefficient	-0.090	-0.223	-0.007	0.003	-0.440	-0.611
SE	(0.158)	(0.175)	(0.185)	(0.205)	(0.306)	(0.369)
Odds ratio						
N	3697	3697	2933	2933	762	762

Note: ***p<.001, **p<.01, *p<.05

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

Odds ratios provide when statistically significant

Table 5. The effect of remediation subject on earnings

	HS graduate comparison group			College student comparison group		
		Propensity score analysis			Propensity score analysis	
Intervention	Bivariate	All observations	Salary greater than zero	Bivariate	All observations	Salary greater than zero
Reading						
Coefficient	8570.99 ***	4796.13 ***	3698.01 ***	-2553.25 ***	52.30	-343.00
SE	(588.07)	(706.76)	(702.27)	(627.25)	(464.55)	(502.32)
N	5583	5583	3838	9935	9935	8012
Writing						
Coefficient	10153.14 ***	5629.65 ***	4441.70 ***	-646.71	914.25	-1.65
SE	(554.90)	(576.32)	(679.79)	(564.52)	(475.75)	(513.12)
N	6284	6254	4447	9935	9935	8012
Mathematics						
Coefficient	9519.42 ***	7138.53 ***	5231.28 **	-1584.55 ***	1159.84 *	811.36
SE	(538.87)	(545.45)	(638.84)	(545.12)	(466.94)	(502.98)
N	6610	6599	4692	9935	9935	8012

Note: ***p<.001, **p<.01, *p<.05

Unstandardized coefficient represents the premium associated with college remediation in dollars.

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

All observations includes those who have a salary of 0.

Table 6. The effect of remediation subject on unemployment

	HS graduate comparison group		College student comparison group	
Remediation subject	Logistic	Propensity score analysis	Bivariate	Propensity score analysis
Reading				
Coefficient	-0.667 ***	-0.355 *	0.169	-0.025
SE	(.097)	(.151)	(.096)	(.102)
Odds ratio	0.513	0.701		
N	5583	5583	9935	9935
Writing				
Coefficient	-0.776 ***	-0.396 *	0.033	-0.100
SE	(.090)	(.165)	(.089)	(.093)
Odds ratio	0.460	0.673		
N	6284	6254	9935	9935
Mathematics				
Coefficient	-0.656 ***	-0.343 *	0.212 *	0.039
SE	(.084)	(.146)	(.084)	(.090)
Odds ratio	0.519	0.709	1.236	
N	6610	6599	9935	9935

Note: ***p<.001, **p<.01, *p<.05

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

Odds ratios provided when statistically significant

Table 7. The effect of any remediation on degree attainment: Remediated students compared with college students not remediated

	All college: remediation vs. no remediation		4-year college: remediation vs. no remediation		Community college: remediation vs. no remediation	
	Bivariate	Propensity score analysis	Bivariate	Propensity score analysis	Bivariate	Propensity score analysis
All students						
Coefficient	-0.468 ***	0.030	-0.298 ***	0.007	-0.236 **	0.095
SE	(0.041)	(0.053)	(.054)	(.063)	(.083)	(.099)
Odds ratio	0.626		0.742		0.790	
N	9935	9935	6280	6280	3633	3633
URMs						
Coefficient	-0.440 ***	0.132	-0.395 ***	-0.043	0.045	0.510 **
SE	-0.081	(0.103)	(.106)	(.126)	(.159)	(.189)
Odds ratio	0.644		0.674			1.665
N	2780	2780	1489	1489	1282	1282
Low SES						
Coefficient	-0.342 **	-0.076	-0.245	-0.216	-0.270	0.004
SE	(0.112)	(0.147)	(.154)	(.120)	(.195)	(.237)
Odds ratio	0.710					
N	1576	1576	687	687	877	877
High SES						
Coefficient	-0.406 ***	-0.053	-0.249 **	-0.042	-0.155	0.060
SE	(.071)	(.086)	(.088)	(.098)	(.158)	(.193)
Odds ratio	0.666		0.780			
N	3697	3697	2933	2933	762	762

Note: ***p<.001, **p<.01, *p<.05

Propensity score analysis uses inverse probability weighting. Trim the dataset when probability of treatment is less than .01 and greater than .99.

Odds ratios provide when statistically significant

Appendix A
Descriptions of variables included in the models

Variable	Variable description
Treatment	
Remediation	
Any	Ever enrolled in college reading, writing, or math remediation
Reading	Ever enrolled in college reading remediation
Writing	Ever enrolled in college writing remediation
Math	Ever enrolled in college math remediation
Dependent vars.	
Earnings	Earnings in 2011, 8 years after high school graduation
Unemployment	Not working at time of survey in 2011; not looking excluded
Bachelor's	Earned a bachelor's degree by 2011, 8 years after high school graduation
Independent vars	
Demographics	
Female	Female
African American	African American
Hispanic	Latino/a
Asian American	Asian American/Pacific Islander
Other Race	Native American, multiple race/ethnicity, other
SES	Socio-economic status composite at senior year in HS. Includes family income, parental education, and job prestige.
Human capital	
Reading test	Reading achievement IRT score in grade 10
Math Test	Math achievement IRT score in grade 12
Highest math-alg	Highest math
Highest math-trig	Highest math -
GPA	HS grade point average: 0=0.00-1.0; 1=1.01-1.5;2=1.51-2.0;3=2.01-2.5;4=2.51-3.0; 5=3.01-3.5; 6=3.51-4.0
Hours studying	Hours/week studying during senior year: 1=none;2=less than 1;3=1-3;4=4-6;5=7-9;6=10-12;7=12-15;8=16-20;9=over 20
Hours working	Hours/week working during senior year: 0=none; 1=1-5;2=6-10;3=11-15;4=16-20;5=21-25;6=26-30;7=31-35;8=36-40;9=over 40
Social capital	
SC composite	Sum of following variables (1=yes;0=no):Parents belong to parent teacher organization (PTO), attend PTO meetings, take part in PTO meetings, act as volunteer at school, belong to other organization with parents from school
Cultural capital	Sum of following variables (1=yes;0=no):Family has daily newspaper, regularly received magazines, has a computer, has access to the internet; has more than 50 books; attended concerts/plays/movies
CC composite	
Habitus	
Expect some college	Expects to attend some college
Expect a bachelors	Expects to earn a bachelor's degree
Need some college	Need some college for job want at 30
Need a bachelor's	Need a bachelors degree or higher for job want at 30

Descriptive statistics of variables included in models

	All		Four year		Community college		No college	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Treatment								
Remediation								
Any	0.295	0.456	0.349	0.477	0.497	0.500	0.182	0.395
Reading	0.145	0.353	0.161	0.368	0.263	0.440	0.136	0.351
Writing	0.197	0.398	0.251	0.434	0.301	0.459	0.091	0.294
Math	0.221	0.415	0.250	0.433	0.393	0.488	0.182	0.395
Dependent vars.								
Earnings	22511.65	24082.61	28193.47	26297.77	20471.67	21529.48	17181.82	29393.29
Unemployment	0.087	0.282	0.061	0.240	0.078	0.269	0.182	0.395
Bachelor's	0.473	0.499	0.631	0.483	0.202	0.402	-	-
Independent vars								
Demographics								
Female	0.516	0.500	0.548	0.498	0.532	0.499	0.591	0.503
African American	0.129	0.336	0.105	0.306	0.127	0.334	0.091	0.294
Hispanic	0.143	0.350	0.083	0.277	0.173	0.379	0.273	0.456
Asian American	0.101	0.301	0.121	0.326	0.105	0.306	0.273	0.456
Other Race	0.056	0.230	0.049	0.215	0.052	0.222	0.045	0.213
SES	0.340	0.446	0.530	0.496	0.241	0.357	0.125	0.329
Human capital								
Reading test	29.944	10.771	35.034	8.948	27.768	9.594	21.003	12.984
Math Test	42.559	24.502	55.484	17.960	38.684	21.198	26.580	24.575
Highest math-alg	0.265	0.441	0.204	0.403	0.375	0.484	0.273	0.456
Highest math-trig	0.459	0.498	0.722	0.448	0.302	0.459	0.182	0.395
GPA	4.063	1.466	4.859	1.061	3.778	1.273	3.091	1.428
Hours studying	3.871	2.024	4.641	1.934	3.658	1.835	3.091	1.743
Hours working	2.803	2.647	2.474	2.285	2.994	2.626	2.636	2.888
Social capital								
SC composite	1.856	1.792	2.318	1.900	1.688	1.674	0.864	1.082
Cultural capital								
CC composite	4.201	1.829	4.784	1.543	4.060	1.804	2.636	1.649
Habitus								
Expect some college	0.162	0.369	0.037	0.189	0.231	0.421	0.455	0.510
Expect a bachelors	0.698	0.459	0.926	0.261	0.671	0.470	0.409	0.503
Need some college	0.123	0.328	0.031	0.174	0.170	0.376	0.136	0.351
Need a bachelors	0.485	0.500	0.661	0.473	0.442	0.497	0.318	0.477