JOURNAL OF RESEARCH IN SCIENCE, MATHEMATICS AND TECHNOLOGY EDUCATION
DOI: 10.31756/jrsmte.613

The Effects of a Mathematics Remedial Program on Mathematics Success and Achievement among Beginning Mathematics Major Students: A Regression Discontinuity Analysis

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Abstract: Proficiency in Mathematics skills is fundamental to success in the STEM disciplines. In the US, beginning college students who are placed in remedial/developmental Mathematics courses frequently struggle to achieve academic success (Fay,2020). Therefore, Mathematics remediation in college has become an important concern, and providing Mathematics remediation is a prevalent way to help the students who may not be fully prepared for college-level courses. Programs vary however, and the effectiveness of a particular remedial Mathematics program must be empirically demonstrated. The purpose of this study was to apply the sharp regression discontinuity (RD) technique to determine the effectiveness of the Jack Leaps Summer (JLS) Mathematic remediation program in supporting improved Mathematics learning outcomes among newly admitted Mathematics students in the South Dakota State University. The researchers studied the newly admitted Fall 2019 cohort of Mathematics majors (n=423). The results indicated that students whose pretest score was lower than the cut-off point and who were assigned to the JLS program, experienced significantly higher scores on the post-test (Math 101 final score). Based on these results, there is evidence that the JLS program is effective in meeting its primary objective.

Keywords: *Mathematics remedial program evaluation; Quasi-experimental research design; Regression discontinuity design; Cohort studies, Causal inference*

Introduction

Accountability is essential for educational institutions (Deming & Figlio, 2016). Institutional effectiveness is gauged in large part on the basis of student leaning outcomes. Many entering students, however, are not fully prepared for success. For this reason, post-secondary educational institutions have introduced a considerable number of remedial/developmental programs in the areas of Mathematics, Reading, and Composition to assist under-prepared students to succeed(Jacob & Lefgren, 2004). Remedial education, accounts for almost one-third of post-secondary courses offered in the US (Bettinger &Long, 2004). Further. 40% to 60% of beginning college students run into difficulties concerning lack of sufficient academic preparation in Mathematics for college-level courses (Snyder, et al.2019, de Brey, & Dillow, 2019; Fusaro, 2007). Mathematics is an “instrumental subject”, which is intertwined with other content areas, and which provides foundational knowledge and skills for Science, Technology, Engineering, and Mathematics (STEM), Art, Business, and Medical Science, etc. Prospective college students who are academically under-prepared in Mathematics who perform poorly on the college placement test are typically placed in remediation or developmental education programs (Sanabria et al., 2021). This in turn may discourage the student’s overall confidence in pursuing STEM majors in particular and may also impede degree progression and time to graduation (Hodara,2013).

The mastery of Mathematics skills is fundamental to success in the STEM disciplines. There are many reasons why students have difficulty pursuing STEM-related majors including inferior performance on the Mathematics placement test and uninspiring introductory Mathematics courses. For example, some high performing students complain that boring introductory courses cause them change majors; meanwhile, underperforming students with high interest mention barriers such as Mathematics placement tests, the Mathematics skill level required for entry-level STEM courses, and also an undesirable class atmosphere that scares them away (Boatman & Bennett, 2021). In 2012, the President's Council of Advisors on Science and Technology recommended that post-secondary institutions generate one million more college students in STEM disciplines over the course of the next decade if the US were to stay competitive in science and technology (Exec. Order No.13621, 2012). The President's Council pointed out that the number of STEM-related students must increase about 34% annually to meet this goal as compared to the current rate of 8 % (86,800 degrees).At present, this goal still has not been met. Quite recently (February 17th, 2022), the White House Office of Science and Technology issued a policy statement intended to direct and broaden participation in STEM fields by encouraging STEM research infrastructure and thereby attempting to guarantee societal benefits from the STEM field innovation. By way of background, according to a White House report generated in 2019, 20% of high school students at that time indicated being interested in STEM-related majors (Herman, 2019). In 2018 the Organization for Economic Co-operation and Development (OECD report indicated that at that time according to data from the Program of International Student Assessment (PISA) program, the US ranked 31st of seventy-nine countries in Mathematics, and 11th in science. PISA is regarded as one of the most challenging worldwide tests and is administered every 3 years. It assesses skills in Reading, Mathematics, and Science literacy for K-12 students (NCES,2018). In 2019, the National Center for Educational Statistics reported that the average scores in Mathematics for K-4, K-8, and K-12 have increased by 0.4%,0.3%, and 0.6% respectively compared to 2018(NCES,2019). This 2019 NCES report, however, also indicated that almost 67% of -year community college-level students had taken at least one course in remedial/ developmental education, while one third of the students in 4-year public colleges had taken at least one such course.

In the US, beginning college students who are placed in remedial/developmental Mathematics courses frequently struggle to achieve academic success (Fay, 2020). Additionally, approximately 25% of four-year school attendees drop out of remedial Mathematics programs. In fact, only 37% of remedial Mathematics students at four-year institutions complete their introductory college courses and 75% of students in remedial Mathematics classes/programs fail to graduate (Flaherty, 2021). Therefore, the efficacy of Mathematics remediation in college has become an important topic. The number of students who require remedial Mathematics courses in college has increased over the course of the past two decades (John et al., 2017). Further, remedial education costs the U.S economy about $1.3 billion annually (Belfield et al., 2016; Jenkins & Boswell, 2002; Jimenez et al., 2016; Tierney & Garcia,2011; Martinez & Bain, 2014).

At issue is how to set valid placement criteria to effectively match student needs with available resources to place students in correct Mathematics remediation programs or introductory college Mathematics courses. Generally speaking, the term "Mathematics remediation" refers to a program designed to assist students who are deficient to perform insufficiently prepared for introductory college-level Mathematics courses (Schak et al., 2017). The purpose of such a program is to refresh or remediate the Mathematics knowledge and skills expected to have been mastered in high school and to cultivate students' learning habits and self-efficacy to aid them in succeeding in college-level Mathematics courses (Valentine et al., 2017). The specific standards for placing less prepared students in remediation programs differ from institution to institution but are based on the student's Mathematics placement test scores. Historically, prospective students have been required to take the Scholastic Aptitude Test (SAT) or American College Testing (ACT) prior to applying for admission. Recently, the COMPASS Algebra test, Assessment and Learning in Knowledge Spaces (ALEKS) online Mathematics Placement Exam, and ACCUPLACER practice test have become more widely adopted for Mathematics placement purposes. Again, the specific cut-off score for requiring that students take a remedial course or enter into a remedial program varies by state and/or by university. Thus, some states may set specific cut-off requirements for all institutions of higher learning as is true in South Dakota, Colorado, Montana, Utah, Washington, Tennessee, and Florida for example, or there may be specific system-level policies (e.g., California State University system), or by the institution-level policies (Calcagno & Long, 2008). For example, institutions in Tennessee set the cut-off score as 26 for the ACT's Mathematics subject area score. Students who score below 26 on the ACT's Mathematics subtest are required to take the COMPASS Algebra test. Students who score 50 or above on the COMPASS test are allowed to enroll a non-remedial course - typically college algebra. On the other hand, students who score below 50 are placed into the developmental mathematics course (Boatman & Bennett, 2021). At some institutions, the ALEKS online Mathematics Placement Exam is employed to place students, except for the students who wish to be in Mathematics for whom different cut-off scores apply (Moss et al., 2014; Pietro, 2012).

There is a considerable debate concerning the efficacy of remedial programs in Mathematics and the extent to which they benefit underprepared students (Yolak et al.,2019). There is little evidence showing how specific Mathematics remedial programs may be directly associated with positive gains in student learning outcomes. Some advocate that remedial education programs are necessary to aid the less-prepared students entering college(e.g., Bettinger &Long,2009; Lesik,2006; Moss& Yeaton,2006; Torraco, 2014). Others opine that remediation is a barrier that results in lower rates of students' retention (e.g., Brothen & Wambach, 2004; Calcagno & Long,2008; Lagerlöf & Seltzer,2009; Martorell & McFarlin,2010; Toll & Van Luit, 2013). Others point out that there is evidence of negative emotional outcomes for students who participate in remedial courses and/or programs as such involvement can be associated with low self-esteem and feeling looked down upon by peers and faculty (Joseph,1992; Nussbaum & Dweck,2008).

Bettinger & Long (2009) analyzed the effect of Mathematics remedial courses on a sample size of 8,600 students at non-selective, four-year colleges in Ohio by means of a conditional logit model. The results indicated that the remediation students had lower chance to drop out or transfer to other schools than non-remediated students did, suggesting that the Mathematics remediation courses may function to increase retention. Using a Regression Discontinuity Design, Lesik (2006) evaluated the effectiveness of a Mathematics remediation program at a private, four-year university located in Northeastern US. The results showed that the program was supportive in enhancing beginning students' achievement in their college-level Mathematics courses. Similarly, Moss and Yeaton (2006) examined the effects of an English remedial course provided in a community college by utilizing a Regression Discontinuity Design. Their results drove the conclusion that the students who participated in the English remedial program earned higher scores in English courses compared to students who did not participate in the program.

There is, however, conflicting evidence. Using an RD design with using longitudinal data, Martorell and McFarlin (2010) found no evidence to indicate that a Mathematics remediation course was beneficial. Calcagno and Long (2008) also used the RD design in a study that included 28 community colleges in Florida. These results utilizing students' scores on the Florida College Entry Level Placement Test (CPT), found evidence that remedial programs increased the student retention, but found no evidence to show a significant impact on the graduate rate. Lagerlöf and Seltzer (2009) employed the Difference-in-Differences (DiD) methodology using panel data and found no significant effect of the Mathematics remedial course on performance in economics courses. DiD design is a methodology that compares before and after treatment differences outcomes. Valentine et al. (2017) conducted a meta-analysis of RD design studies to assess the broad efficacy of placement in developmental education. The results, however, were not as expected - students who were assigned to the remedial program actually performed more poorly in the college courses and earned fewer college credits after about three years compared to their peers who did not participant the programs. Taken together, the evidence would seem to suggest that the efficacy of remedial programs may very well depend upon the specific nature of the programs employed. The question of what type of programs may be successful and the implications for best practices recommendations remains unresolved at preset. Therefore, additional research is needed.

Different universities and colleges in the United States use a wide variety of placement instruments to assign students to developmental education classes and programs, such as standardized tests, high school academic transcripts, and surveys (CCCCO, 2011). The South Dakota Board of Regents has issued Mathematics placement guidelines for public universities (SD Developmental Education Policies, 2018). The guidelines include an index score matrix which takes into account students' high school GPA and assessment scores. Approved assessment scales include, among others, the ACT, ACCUPLACER, SAT and Smarter Balanced.

Setting

The Jack Leap Summer (JLS) program has been in use at South Dakota State University continuously since 2017. (The name of "Jack Leaps" originated from SDSU's Mascot— a Jackrabbit). It is a Mathematics remedial program and aims to assist newly admitted college students who are preparing for their Mathematics placement test. JLS is free of charge to newly admitted students in all Majors that require the Mathematics placement test. JLS lasts for eight weeks and requires the participants to be involved in the program from the beginning of June and to the beginning of August.

As SDSU policy, all the incoming students admitted to STEM-related, or Business degree programs are required to take the Mathematics placement test utilizing the Assessment and Learning in Knowledge Spaces (ALEKS) software package before May 31st for the Fall semester and Novemeber 30th for the Spring semester every year. These results are used to determine which Mathematics course will be taken in the Fall. ALEKS is a nationally recognized placement tool that can be accessed at any time online and for which the students have 48 hours to complete the test. The test usually is comprised of 25 to 30 questions. The possible range of ALEKS scores is 0 to 100. By policy, if the score is above 76% overall with 56% in the Trigonometry section, the student passes the Mathematics placement test and can take the entrance level Mathematics course, Math 101, in the Fall. Students who score below a total score 76and below 56 in the Trigonometry section, are invited to participate in the JLS program. For the present analysis, the control group was comprised of students whose total score was over 76 and 56 or above in Trigonometry. . There were no students who scored above 76 and below 56 in Trigonometry.

The JLS program consists of intensive pre-calculus reviews with four Leap Mentor groups and provides three delivery formats - face-to-face, hybrid, and online. Each mentor group consists of one full-time faculty member and one part-time faculty member who teach college-credit Mathematics classes at SDSU, along with two graduate teaching assistants who are majoring in Mathematics or Mathematics-related majors. The “A” group focuses on the topic of intermediate Algebra; the “B” group emphasizes Trigonometry; the “C” group is for College Algebra and “D” is for Mathematics reasoning. The participants are assigned to one or more of four groups based on the results of the ALEKS. Weekday mornings (Monday through Friday) from 8:30 am to 11:00 am each Mentor group devotes 2.5 hours for lectures taught by the full-time instructor, while afternoons from 2:00 PM to 5:30 PM are devoted to exercises using the ALEKS software package. Part-time instructors and graduate teaching assistants are available to offer individual firsthand explanations and assistance. Participants can discuss with each other and ask questions of the part-time instructor and graduate assistants. The instructors can assign the students some homework outside of the ALEKS and offer inquiry-based instruction.

The specific goal of JSL program is to prepare students for their math placement test, but the ultimate goal is to enable students’ future math success during their entire undergraduate journey. Therefore, the final grade in Math 101 seems the proper way to compare the whole cohort of students from Fall 2019 who took part in the JLS program with those students whose background is strong enough to enroll in Math 101 directly. The results of the first placement test are used to triage the students. Those that pass can move directly to Math 101; those that do not, can either take a remedial course or participate in JLS. After doing so in either case students take the placement test a second time to determine if they are ready for Math 101. Therefore, ultimately, all students must receive a passing grade to move to Math 101.

In view of the fact that there are few studies of the effectiveness of remedial education programs that are based on methodologies that permit valid causal inference and that this is particularly so in the field of Mathematics education, the purpose of the present study was to apply the Regression Discontinuity (RD) technique to determine the effectiveness of the Jack Summer Leaps program in supporting improved Mathematics learning outcomes among newly admitted Mathematics students in the South Dakota State University. Toward this end, we studied one cohort of Fall 2019 at SDSU to determine whether the cut scores currently in use for the placement exams are set correctly and to assess the efficacy of the program overall.

Methods

Participants

Among 10,200 new rising students for the Fall 2019 cohort who were required to take the Mathematics placement test, there were 491 students who declared a major in Mathematics. This Fall 2019 cohort of newly admitted Mathematics majors constituted the population of interest. Of these here were 54 students who did not pass the Mathematics placement test but who chose not to participate in the JSL program; 14 students withdrew from the JSL program without completing, resulting in the final sample size of 423 for this analysis. According to the WWC attrition rule and the regression discontinuity design standards, the authors calculated the overall attrition as 13.8% and the differential attrition is 10.1%. Under the cautious threshold, the maximum allowable differential attrition is 6%. Therefore, this is high attrition. However, under the optimistic threshold, the maximum allowable differential attrition is 10.9% points, thus fitting within allowable parameters.

Study Design

The Regression Discontinuity (RD) design was utilized to create comparison groups based on students' scores on the required ALEKS placement test. The highest possible score is one hundred. A score of 76 or above is considered passing. Accordingly, a cut-off score of 76 was utilized in the present analysis to create two discrete groups for comparison purposes. Students at the margin, within **n** points above or below this cut-off were randomly assigned to the one of the two comparison groups to account for measurement error (systematic error and random error).There were 288 students who in the treatment group and 135 in the contrast group. The researchers were authorized to utilize de-identified student-level administrative records provided by the Mathematics department of South Dakota State University which tracked student progress along several dimensions. Based on the 76/100 cutoff points on the post-test, the authors separated the dataset based on the second placement test results. Specifically, if lower than 76, assignment was to one group whereas if higher than 76, then to the other group irrespective of t scores on the first placement test.

Based on the research question, the dependent variables of interest were the final scores in Mathematics 101, the entry-level Mathematics course, and scores on the Mathematics portion of Assessment and Learning in Knowledge Spaces (ALEKS), an online assessment and learning platform which assesses, Mathematics content proficiency in pre-Algebra, Algebra 1 and 2, geometry.

Procedure

The two hypotheses were evaluated based on the research questions as follows:

H0:

$\beta_1 \neq 0$ (The cutoff point is either set too low or too high)

$\beta_2 = 0$ (There is no mean difference between the treatment and control groups utilizing the current minimum passing score as the cutoff point (76 out of 100).

H1: $\beta_1 = 0$ (The cut off point for the placement exams were set appropriately).

H2: $\beta_2 \neq 0$ (There is a significant difference between the treatment and control groups based on the cutoff point (76 out of 100).

The JSL program used the students' 1st ALEKS Mathematics placement score to refer for remediation. Based on the sharp RD design requirement, students whose scores fell below the cutoff of 76 were assigned to treatment group (T=1), while the control group was comprised of students who achieved scores at or above the cutoff (T=0). In this case, the treatment effect would be considered to be a discontinuous function of the Mathematics placement score: T=1($X < 76$). Under the present assumptions, the potential outcome *Y* is the continuous function of the running variable (i.e., 1st Mathematics placement score) at the cutoff, and no other alternative unexplained discontinuity relationships of treatment assignment other than at the cutoff are apparent. The causal effect of the JSL program on students' posttest scores within the local neighborhood of cutoff ***C*** could be correctly evaluated using RD. With this expectation in mind, the initial model for regression discontinuity was as follows:

$Yi = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i Z_i + \beta_4 X^2_i + \beta_5 X^2_i Z_i + Ei$ where

Yi = Entrance College level Mathematics course (Mathematics 101) for the *ith* score,

β_0= Coefficient for control group y-intercept at cutoff (76 out of 100),

β_1 = Linear coefficient of the transformed score (pretest score - cutoff score: 1st Mathematics placement score – 76),

β_2= Coefficient for the JSL program effect estimate(coefficient for the mean difference between treatment and control groups),

β_3 = Linear interaction coefficient of the interaction product of X_iZ_i,

β_4 = Quadratic transformed pretest coefficient,

β_5 = Quadratic interaction coefficient of the interaction product of $X^2_i Z_i$,

Xi= Transformed pretest: raw score – (76),

Zi = Dummy variable for treatment (1 = treatment and 0 = Control),and

Ei= Residual for the ith score.

Under a well-designed placement policy, one would expect that the results of the RDD models would yield placement coefficients(β_1 in our study) near zero (Robinson, 2011). If the placement coefficients(β_1) were positive, then the results indicate that the students near the cutoff point are benefiting substantially from the placement policy, and that the set cut score has to be set higher in case students whose score is just above the cutoff point can also be placed in the JSL program; Similarly, when the placement coefficients are negative, students at the margin are not benefiting from being placed in JSL program, therefore, the cut off scores need to be lowered, so that these students can be placed to the college level course directly(Melguizo et al.,2015).

Results

Descriptive Statistics

Data analyses were conducted in R (R-4.2.1). Table 1 depicts the summary descriptive statistics for the JSL 2019 cohort students' scores on the Mathematic placement. For the control group of 135 students, the mean was 87.12 (S.D.= 4.87), the skewness and kurtosis values are -0.27 and -0.67 respectively and are comparable to those for the treatment group. Therefore, normality of variance assumptions is considered to be satisfied.

Table1

Summary of descriptive statistics of first Math placement test score

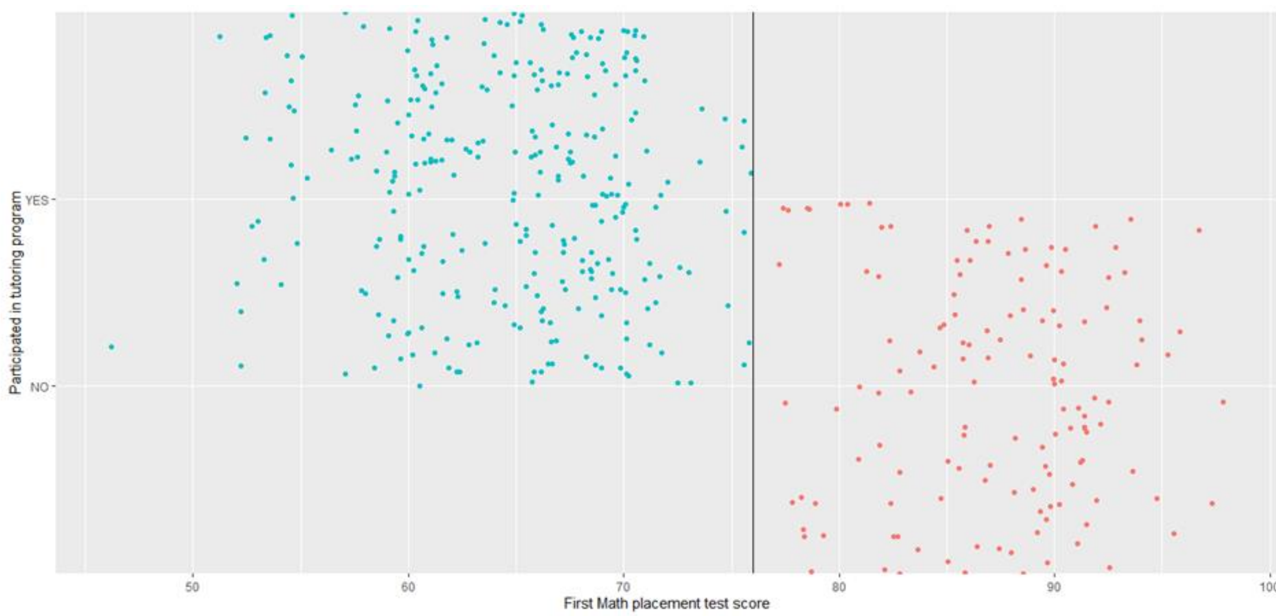
Group	N	Mean	Median	S.D.	Skew	Kurtosis	S.E	Range
Treatment(<=76)	288	64.61	66	5.47	-0.4	-0.23	0.32	29
Control(>76)	135	87.12	88	4.87	-0.27	-0.67	0.42	20

Scatter Plot of Group Dispersion

Figure 1 illustrates a scatter plot of how the two groups of students were distributed based on the established cutoff point (76 out of 100). Students who scored under seventy-six participated in the JSL program, and students who scored above 76 did not in the program.

Figure 1

Scatter Plot of Group Dispersion



Note: Green dots represents the JLS participants; red dots represent the students who were not in the JLS program.The vertical line between 70 and 80 in the Y axis (First Math placement test score) is the cutoff point(76/100).

Because program participation was voluntary, some students whose Mathematics placement test score were close to seventy-six may have declined participation in the program and some students may have joined the program who were not required to do so. Therefore, local polynomial density estimation showed the results in Table 2. The upper-left panel gives basic summary statistics on the data separately for control ($Xi < 76$) and treatment groups ($Xi \geq 76$). This table also indicates the value of the bandwidth(s) chosen. The upper-right panel includes general information regarding the overall sample size(N=423) and implementation choices of the manipulation test. The lower panel reports the results from implementing the manipulation test: the test statistic is constructed using a $q = 3$ polynomial, with different bandwidths chosen for an unrestricted model with polynomial order $p = 2$. Specifically, the bandwidth choice is located at 23, leading to effective sample sizes of $N- = 280$ and $N+ = 138$ for control and treatment groups, respectively. The final manipulation test is $Tq= 1.2596$, with a p-value of 0.2078. Therefore, in this application, there is no statistical evidence of systematic manipulation of the first Mathematics placement test scores indicating that we met the RDD prerequisite.

Table 2

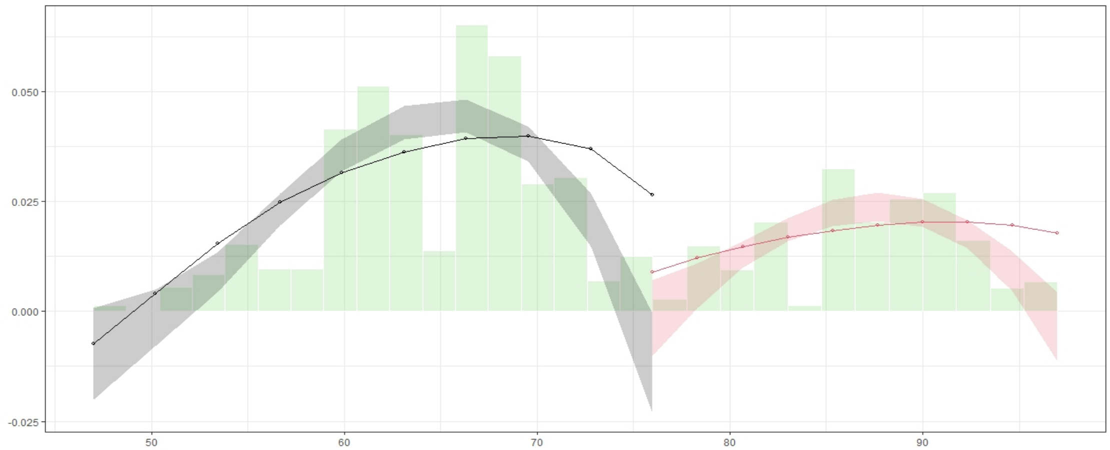
RD Manipulation Test using local polynomial density estimation

Cutoff C=76	Left of C	Right of C	Number of obs	423
Number of obs	285	138	Model	Unrestricted
Eff. Number of obs	280	138	BW method	Estimated
Order est.(p)	2	2	Kernel	triangular
Order bias(q)	3	3	VCE method	Jackknife
Bandwidth est.(h)	23	23		
Running variable	First Mathematics placement test scores			
Method	T	p>|T|		
Robust	1.2596	0.2078		

As can be seen in figure 2, the manipulation test plot that shows that the confidence intervals overlap substantially.

Figure 2

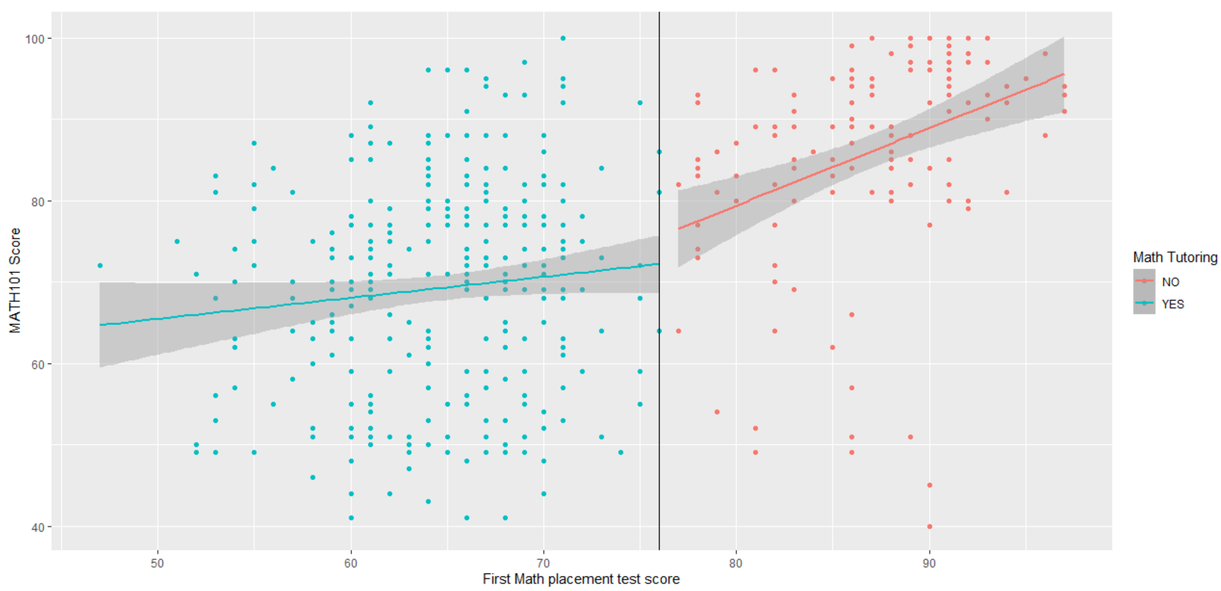
Manipulation test plot



The last main preliminary check required the researchers to visually examine the discontinuity effect using a bivariate scatterplot depicted in Figure 3.

Figure 3

Bivariate distribution of Mathematics 101 scores



In figure 3, the green line depicts the predicted performance of students in the tutoring program while the orange line represents the predicted performance of students in the absence of the program. A treatment effect is indicated if there appears to be a "discontinuity" or "jump" between the two regression lines at cutoff (Xi=76). Indeed, in this case, the scatter plot reveals such a "jump" in the regression lines at the cutoff point demonstrating the treatment effect of the participation in the Mathematics tutoring program on the posttest (Math 101) scores quite clearly. Students who took part in the Mathematics tutoring program experienced a slight increase in their Mathematics 101 scores. From the scatterplot, there do not appear to be flexion points, but the researchers included all order terms (e.g., interaction, quadratic, and quadratic interaction terms) in the initial model to avoid underspecifying the RD model.

Before running the regression discontinuity analysis, the researchers constructed data coding for ease of interpretation. Table 3 presents the numerical codes pertaining to data in the analysis Tables.

Table 3

Coding in the RDD Data Analysis

Column Heading	Definition
PRE	Pre-assignment variable (First Mathematics placement test score)
tutoring	Binary Group membership (YES/NO)
TUTORING	Binary Group membership(1/0)
PRE_centered	Transformed assignment variables(PRE-76)
PRE_centered_sq	Quadratic term
PRE_centered_interaction	Linear interaction term
PRE_centered_sq_interaction	Quadratic interaction term

Table 4 reveals the results of the simplified model(Model 1) without the quadratic and interaction terms. This adjusted model explains 28.9 % of the variance in the outcome variable (Math 101 score), $F(2, 420) = 85.5$, $p < .001$, $R^2 = .286$. The treatment effect estimated for in this model is -6.872 (SE=3.003), p=0.022.

Table 4

Regression Results for Model 1 (Simple model without Quadratic and interaction terms)

Model	Estimate	Std.Error	t value	Pr(>|t|)
Intercept	81.176	1.7312	46.89	<0.001
PREcentered	0.446	0.1192	3.74	<0.001
tutoringYES	-6.872	3.003	-2.288	0.022

Note: $R^2 = .289$ R^2(adj)=.2859; F(2,420)=85.5,p<0.001

In order to make sure the Model 1 was not underspecified; the researchers included the interaction term based on Model 1 in the second model. Model 2 explains 30.6 % of the variance in the outcome variable (Mathematics 101 final score), $F(3, 419) = 60.02$, $p < .001$, $R^2 = .306$. (See Table 5). However, Model 2 showed the treatment effect(tutoringYES) was not significant with p=0.3.

Table 5

Regression Results for Model 2 (Simple model with interaction term)

Model	Estimate	Std.Error	t value	Pr(>|t|)
Intercept	75.567	2.763	27.352	<0.001
PRE_centered	0.95	0.228	4.173	<0.001
PRE_centered_interaction	-0.6914	0.267	-2.594	0.009
tutoringYES	-3.393	3.271	-1.037	0.3

Note: $R^2 = .306$ $R^2(adj)=.29$; $F(3,419)=60.02, p<0.001$

Table 6 shows the results of integrating the linear and quadratic terms and their associated interactions. Results indicated that the full model predicted 30.9 % of the variance in the Mathematics 101 scores, $F(5,417)=35.98, p<0.001$, with an $R^2 = .309$. The primary effect of interest is the treatment effect estimate for those who receive the treatment, which is -4.899 (SE=5.413) for this model. However, examination of the full model does not show tutoring variable (tutoringYES) or other interaction and quadratic terms to be significant. Therefore, the non-significant terms should be eliminated from the model 3 and the model 1 is the best fit.

Table 6

Regression Results for Model 3 (Full model with Quadratic terms)

Model	Estimate	Std.Error	t value	Pr(>|t|)
Intercept	76.068	4.476	16.994	<0.001
PRE_centered	0.827	0.893	0.926	0.355
tutoringYES	-4.899	5.413	-0.905	0.366
PRE_centered_interaction	-0.769	1.032	-0.746	0.456
PRE_centered_sq	0.006	0.041	0.142	0.887
PRE_centered_sq_interaction	-0.014	0.045	-0.304	0.761

Note: $R^2 = .309$ $R^2_{(adj)}=.2925$; $F(5,417)=35.89, p<0.001$

Therefore, the authors removed the quadratic and interaction terms to achieve the best possible model fit. The final model(Model 1)is depicted in Table 4 above. With the linear interaction term eliminated, the equation for the best fitting model. Model 1 becomes:

$$Yi= \beta_0+ \beta_1 Xi+ \beta_2 Zi + Ei$$

The null and alternative hypotheses of interest were $\beta_1 \neq 0$ (The cutoff point was either set too low or too high), with the alternative hypothesis of $\beta_1 = 0$ (The cut off point for the placement exams was set appropriately), the other null hypothesis was $\beta_2 = 0$, with the alternative hypothesis of $\beta_2 \neq 0$. Given this formula, $\beta_1 = 0.446$, $\beta_2 = -$

6.872.Mathematics 101 final scores (post test scores) are equal to 81.176 + 0.446* PRE_centered - 6.872*tutoringYES. β_0 (intercept) reveals the average Mathematics 101 score at the 76 cut off point. Specifically, students whose first Mathematics placement test score was 76.01 points (above 76) on the entrance exam scored an average of 81.176 points on the Mathematics 101 final exam. β_1 is the coefficient for transformed variable (first Mathematics placement test score -76). For every point above 76, that students scored on the first Mathematics placement test, their score will be increased by 0.446 points on the Mathematics 101 final exam. The positive coefficient for β_1 indicates that the students near the cutoff point benefitted substantially from the placement policy and the cutoff point should be leveled up, so that those students whose score are just above the cut-off (76) can also be placed in this JSL program. β_2 is the coefficient for the tutoring program (JSL) estimate effect. Students whose placement test scores were lower than seventy-six and who participated in the tutoring program would be projected to see their Mathematics 101 final grade score decrease by 6.872 points.

Sensitivity Analysis

The researchers next compared different bandwidths (for example: ±3 points, ±5 points or ±10 points) to fit the best-fitting model (Model 2). Table 7 shows the comparison results of the three different bandwidths (±3, ±5, or ±10 points). The effect of tutoring varies across these four adjusted models, from -6.872 to -14.254, but one common result is that the coefficient remains negative in all models, and only in the full data model is the effect significant. The sample size also becomes smaller when the bandwidth gets narrowed, down from 206 to 27.

Table 7

Simple model with different Bandwidth

Model	Full data	Bandwidth = 3	Bandwidth = 5	Bandwidth = 10
(Intercept)	81.176***	75.142***	81.617***	80.134***
	(-1.731)	(-6.542)	(-4.394)	(-2.884)
PRE_centered	0.446***	1.895	-1.158	0.164
	(-0.119)	(-2.663)	(-1.085)	(-0.349)
tutoringYES	-6.872*	-4.363	-14.254+	-8.498
	(-3.004)	(-10.521)	(-7.942)	(-5.173)
Num.Obs.	423	27	56	206
R^2	0.289	0.191	0.077	0.12
F	85.497	2.827	2.202	13.801
RMSE	12.94	12.59	13.46	13.36

Note: + p < 0.1, * p < 0.05, ** p < 0.01,
***p < 0.001

Another common approach to sensitivity analysis is to use the ideal bandwidth, twice the ideal, and half the ideal, and see if the estimate changes substantially (Imbens & Kalyanaraman, 2012). The researchers employed non-parametric estimation to get the ideal bandwidth based on one common MSE-optimal bandwidth selector for the RD treatment effect estimator(see Table 8). Table 8 reveals the actual effect size of the discontinuity. The coefficient of method "conventional" is 14.551, which indicates that the tutoring program caused a 14.55 point increase in the Mathematics 101 final score, (p =0.053). The model used the ideal bandwidth of 6.77 (BW est. (h) in Table 8), which means it only considered students with test scores of 76 ± 6.77. The model used a triangular kernel. The kernel allocates how much weight is given to observations surrounding the cutoff. For example, test scores such as 75.99 or 76.01 are extremely close to 76, so they receive the most weight while scores such as 65 or 70 are a little farther away from the cut off, so they matter less. The researchers also used different kernels to compare the actual effect size of the obtained discontinuity.

Table 8

Ideal bandwidth on BW type =mserd

Cutoff C=76	**Left of C**	**Right of C**	**Number of obs**	423
Number of obs	285	138	BW type	mserd
Eff.Number of obs	54	31	Kernel	triangular
Order est.(p)	1	1	VCE method	NN
Order bias(q)	2	2		
Bandwidth est.(h)	6.77	6.77		
Bandwidth bias(b)	11.819	11.819		
rho(h/b)	0.573	0.573		
Method	**Coef.**	**P>|z|**		
Conventional	14.551	0.053		
Robust		0.07		

The coefficients of effect size changed sufficiently as depicted in Table 9. The left panel shows no significant effect size across the different bandwidths; the right panel indicates the effect size changed significantly between 15.396 and 18.24 (medium treatment effect) when switching the kernel type to Epanechnikov (more distant observations have less weight following a curve) and Uniform (unweighted and more distant observations have the same weight as closer observations).

Table 9

Effect size of discontinuity Comparison

Bandwidth	Effect size	Kernel	Bandwidth	Effect size
6.77 (ideal)	14.551	Triangular	6.77	14.551
13.54 (twice)	8.75	Epanechnikov	6.367	15.396*
3.385(half)	-0.046	Uniform	5.223	18.24*

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion

This study provides a practical evaluation of the postsecondary Mathematics remedial program (JLS) at South Dakota State University to assess the effectiveness of the JLS program in supporting improved Mathematics learning outcomes among newly admitted Mathematics students. Moreover, it also describes the preliminary analysis (bivariate distribution scatter plot and local polynomial density estimation) to assess the assumptions of RDD and determine if this research design is the appropriate method for such analysis. The results have the potential to inform future research addressing the effectiveness of similar remediation programs. Conceptually, the research questions were well suited to the RDD method of an observable continuous running variable (first Mathematic placement test score), a clear assignment cut-off point(76 out of 100) and proved non-manipulation for assigning students who scored near the cut-off point into the JSL program. While remedial education constitutes a major investment for many colleges and universities, the literature provides truly little information about the causal impact of remedial courses, and what little evidence exists is conflicting. This study helps to clarify conflicting evidence concerning the effectiveness of Mathematics postsecondary remediation discussed earlier.

In order to accomplish this, the researchers exhausted three models (model 1,model2, and model 3) to specify through adding the interaction terms, quadratic terms, and only the results of the simple model without quadratic and interaction terms (Model 1) were significant. The findings indicated that for every point above 76 that students score on the initial Mathematics placement test, their score will be higher by 0.446 points on the Mathematics 101 final exam. $\beta 2$ is the coefficient for the tutoring program estimate effect and we should care most. Students whose first test score was lower than 76 and who took part in the tutoring program can be expected to experience an increase of -6.872 points in their Mathematics 101 final grade. This finding is consistent with previous studies Martorell &McFarlin,2010; Calcagno & Long,2008;Lagerlöf & Seltzer, 2009; Valentine et al., 2017; Melguizo et al.,2015; Baranyi & Molontay,2021) which reports similar but less pronounced effects of Mathematics remedial programs.

An unexpected finding in the present study was that the control group students who did not participant in JSL actually performed better than did the JSL students in the entry-level Mathematics class (Mathematics 101). A possible reason for this unexpected finding may be that those students who participated in the JLS program had become familiar with the initial testing and were also highly motivated to pass the second administration as this would allow them to register for the first non-remedial Mathematics course which would count to their degrees. When they were subsequently enrolled in Mathematics 101, however, their background was still not strong enough to perform well on assignments and tests. Moreover, non-remedial college courses typically involve a variety of assignments, projects, tests, quizzes, etc., often with different weights to comprise the final course grade. In the present instance, therefore, it is possible that the final grade in Mathematics 101 as a posttest measure may not have been sufficiently sensitive to assess the effectiveness of the JSL program, whereas Math 101-course covered all the algebra and trigonometric knowledge in the ALEKS, the instructors may teach differently and may have different assignments, but the final exam format should be the same or at least at the same difficulty level. However, as we mentioned in the discussion, there will only be a final grade for Math101, which consists of other assignments, attendance requirements, quizzes, and 3 midterms comprehensively. We cannot evaluate the students' performance just based on one single exam. Therefore, to perform well in the first Mathematics course, other variables are certainly involved such as the need to attend class regularly, practice mathematics skills more often, prepare diligently, request help when needed, etc. Therefore, future research may wish to focus on students' study patterns, institutional policies, and classroom strategies, as these may moderate or mediate the effectiveness of the intervention. It is also noted that the covid-19 pandemic has broadened pre-existing opportunity and achievement gaps, hitting historically disadvantaged students hardest. Student assessment data from 2019-2021 shows evidence of substantial incomplete learning among students. Mathematics performance shows large losses among K-12 students, and many learning outcomes show more modest growth trajectories than before the pandemic (Dorn et al. 2021). When students progress or enter college without solid foundations in STEM knowledge, we squander the chance to move them to the cutting-edge of STEM fields. Therefore, the fallout from the pandemic highlights the importance of evaluating the effectiveness of remediation program as never before.

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Please Cite : Du, K., & Lipscomb, T. J. (2022). The Effects of a Mathematics Remedial Program on Mathematics Success and Achievement among Beginning Mathematics Major Students : A regression discontinuity analysis. *Journal of Research in Science, Mathematics and Technology Education*, *6*(1), 21-39. DOI: https://doi.org/10.31756/jrsmte.613

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics Statement: This study was approved by the Institutional Review Board at the university of southern Mississippi and the researchers were authorized to utilize de-identified archival student-level administrative records provided by the Mathematics department of South Dakota State University which tracked student progress along several dimensions. There are no human subjects in this article and informed consent is not applicable.

Author Contributions: The authors confirm contribution to the paper as follows:

Study concept or design of the article: Thomas J. Lipscomb & Kuixi Du. Data Acquisition: Kuixi Du. Data analysis and interpretation: Kuixi Du. Draft manuscript preparation: Kuixi Du. Revise critically for important intellectual content: Thomas J. Lipscomb & Kuixi Du. Supervision and approved the version to be published: Thomas. J. Lipscomb. Agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved: Thomas. J. Lipscomb & Kuixi Du. All authors reviewed the results and approved the final version of the manuscript.

Received: Oct 19, 2022 ▪ Accepted: Jan 14, 2023