Remedial Education Reform in California and Community College Student Outcomes

Alice Li *

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Abstract

The efficacy of remedial education in helping students achieve academic success has long been debated. Between 2013 and 2017, California passed various remedial education reforms, first changing the methodology of remedial education placement, and later removing remedial education mandates altogether. These reforms increased direct access to transfer-level courses for students without first requiring remedial education. I exploit the timing of these reforms to explore how students fare in community college without completing the remediation sequence. I find that the later reforms induced students at all levels of academic preparation to take and pass transfer-level courses at similar or higher rates as students before any policy changes, except for students at the lowest level of academic preparation, who passed at slightly lower rates. Furthermore, the removal of remediation requirements encouraged additional transfer-level course taking, but at a lower completion rate. Overall, removing remediation requirements had positive effects on student success for students at all levels of college readiness, particularly for those on the margin of requiring remediation.

*Alice Li, Email: alice.li@usdoj.gov; U.S. Department of Justice. The views of this paper are my own and do not necessarily represent the U.S. Department of Justice. The research reported here was supported through the generosity of funding from the College Futures Foundation and the Institute of Education Sciences, U.S. Department of Education, Grant R305E150006 to the Regents of the University of California. The research reported here was conducted under research partnership agreements between the University of California, Davis (Michal Kurlaender, PI) and the California Community Colleges Chancellor's Office and the California Department of Education, respectively. I would like to thank Michal Kurlaender, Scott Carrell, and Paco Martorell for providing invaluable guidance and support. The findings and conclusions here are those of the author alone and do not necessarily reflect the positions or policies of the funders, including the Institute of Education Sciences or the U.S. Department of Education, or the data providers.

1 Introduction

Community college is a vital and substantial component of the higher education system in the United States today. In 2021, community colleges enrolled 41 percent of all undergraduates and 39 percent of all first-time college students.[1] In particular, the California Community College system is the largest system of higher education in the United States, enrolling 25 percent of all community college students in the nation.[2] Community colleges have been touted as a cheaper alternative and gateway to four-year colleges (Barrington, 2020), with the potential to help reduce inequities in income and wealth.[3] However, the reality has not been so rosy. Out of the California community college students who stated an intent to transfer or graduate with a degree, only 48 percent were able to do so in 6 years, despite these programs and degrees being meant to be accomplished in 2 years (PPIC, 2019).

One reason cited for these low success rates is remedial education, which has been observed to function more as a roadblock for many students, rather than providing help and support as initially intended (MDRC, 2013). Remedial education, also referred to as developmental education, consists of courses that reteach and reinforce previously taught skills to help improve student outcomes in future college-level coursework. Proponents of remedial education argue that remedial education can give struggling students individualized attention, and build confidence for later college-level courses. Remedial education is extremely widespread, with 80 percent of students enrolling at least once throughout their college journey, and disproportionately affects underrepresented minorities and socioeconomically disadvantaged students with less access to quality college preparation in high school (Cuellar Meija et al., 2016b).

However, despite intentions to support entering community college students considered underprepared,

[1] Fast Facts 2021. American Association of Community Colleges. https://www.aacc.nche.edu/wp-content/uploads/2021/03/AACC_2021_FastFacts.pdf. Accessed 12 Oct. 2021.

[2] Key Facts. California Community Colleges. https://www.cccco.edu/About-Us/Key-Facts. Accessed 12 Oct. 2021.

[3] Mintz, Steven. "Community Collges and the Future of Higher Education." 9 Mar. 2019. https://www.insidehighered.com/blogs/higher-ed-gamma/community-colleges-and-future-higher-education. Accessed 12 Oct. 2021.

descriptive studies have shown that remedial education sequences have had unintended negative consequences, such as lengthening time to degree and encouraging overall attrition (Bautsch, 2013), with many students never advancing to a transfer-level course.[4] This is particularly troublesome, as students cannot access certain college-level courses that are required for graduation or transfer without first finishing their remediation sequence. These statistics also do not take into consideration any possible "discouragement effects," where students who are initially assigned to remedial education are discouraged from enrolling in community college at all (Scott-Clayton and Rodriguez, 2015).

These worrisome statistics motivated the state of California to pass various reforms with the hopes of encouraging and bolstering student success. In 2013, California first passed remedial education placement reforms. Following concerns that these policies were not working as intensely as hoped, California then instituted one of the most sweeping changes to the remedial education system, effectively removing mandatory remedial education requirements altogether in 2017 through Assembly Bill (AB) 705.[5] I use the introduction of these policies as a source of quasi-exogenous variation, to study how remedial education reforms, as well as the complete removal of remedial education, affect community college student success outcomes, particularly with respect to course selection and overall units accumulated.

Although there are numerous descriptive studies regarding AB 705 (PPIC, 2019; Cuellar Meija et al., 2018, 2021), this is one of the only papers that can study the causal effect of AB 705 on students along a continuous measure of college readiness, as opposed to a singular cutoff. My paper has the advantage of being able to use student-level data on college course selection linked to student-level high school data including a rich set of controls. Finally, it is one of few causal papers that can study the effect of increasing direct access to transfer-level courses, joining a collection of papers which study a similar policy change in

[4] In California specifically, attrition is extremely high, with only 44 percent of remedial math students and 60 percent of remedial English students completing the sequence (Bailey et al., 2010; Cuellar Meija et al., 2016b). Only 27 percent of students who take a remedial math course eventually complete a transfer-level math course with a C or better, while 44 percent of remedial English students go on to complete a transfer-level English course (Cuellar Meija et al., 2016b).

[5] What is AB 705? California Community Colleges, https://assessment.cccco.edu/ab-705-implementation. Accessed 24 March 2021.

Florida beginning in 2013 (Park-Gaghan et al., 2020, 2021), and the first to do so with respect to California community college students.

I find that the effective removal of remedial education through AB 705 had larger effects on course selection than the combination of placement reform policies implemented from 2013-2017. Earlier placement reforms did not have large effects on the proportion of students enrolled in remedial English or math. In contrast, there were large reductions in the proportion of students enrolled in remedial courses after AB 705 was passed, concentrated among students with the lowest levels of academic preparation.

In addition, AB 705 had comparatively larger effects on both math and English transfer-level course participation, with students after the removal of remedial education passing both subjects with a C or better at similar or even higher rates compared to students enrolled in community college before any remediation reform. This result holds for students across all levels of academic preparation, except for those deemed least prepared for college. These results are consistent with the motivation for AB 705 legislation, which was to completely eliminate the use of remediation unless deemed necessary.[6]

I find that the students who benefit the most from this increase in direct access to transfer-level courses are students on the margin of being placed into remedial education, and that these beneficial effects decrease but are still positive, as students are deemed to be less and less prepared for college. These results provide support for the previous literature, which has found that students who are most negatively affected by remedial education are those at the margin.

This paper has many policy implications, particularly regarding the future of remedial education. Considering that I find that many students, who would have been placed into remedial education before any reform was passed, were capable of passing transfer-level English or math, suggests that remedial education might not have imparted substantial benefits to those students. Since remedial education is a widespread, but costly intervention, it is important for colleges to understand what sort of benefits or costs are accru-

[6]California State Assembly Bill. Assembly Bill 705: Seymour-Campbell Student Success Act of 2012. SEC 2.78213d(1)(A).

ing as a result of this policy. As colleges nationwide move to restructure and reform remedial education, it is also necessary to understand how these policy changes affect all students across a range of academic needs, and not just at the margin.

2 Literature Review and Policy Background

Causal studies regarding the efficacy of remedial education have not come to a consensus, with studies finding a mix of negative or null effects of remedial education on a large range of student outcomes. Recent papers focusing on four-year college students similarly find mixed results on a myriad of outcomes, including credit accumulation, persistence, degree completion, and labor market outcomes (Bettinger and Long, 2008; Calcagno and Long, 2008; Martorell and McFarlin, 2011; Boatman and Long, 2018; Kurlaender and Case, 2020). A study by Bettinger and Long (2005) finds positive effects of math remediation on math credits completed and the probability of transfer for community college students, but no effect of English remediation on any measure of success, suggesting the importance of studying effects separately by subject.

My paper relates to a strand of literature focused on remedial courses and its effect on college outcomes, and more broadly on how college readiness affects college success. Many papers dedicated to understanding the effect of enrolling in remedial education utilize a regression discontinuity strategy (Calcagno and Long, 2008; Martorell and McFarlin, 2011; Duchini, 2017), which provides great internal validity, but focuses on students at the margin who are potentially the students who would least benefit from remedial education.

A few papers regarding the efficacy of remedial education, such as Scott-Clayton and Rodriguez (2015). Xu (2016), and Boatman and Long (2018), are able to study its effects on students over a range of academic needs. Boatman and Long (2018), like other papers, use a regression discontinuity design; however, they are able to analyze effects of remediation on students who are assigned to different quantities of remedial courses, considered as a proxy for college readiness. Their results suggest that the benefits of remedial courses on students' academic success are dependent on the level of student preparation.[7]

In contrast, Xu (2016) finds that students who required the most remediation faced the largest negative effects. Using regression discontinuity to study students on the margins of requiring different levels of remedial courses, Xu (2016) finds that students who required the lowest level of remedial education were more likely to drop out of college and, consequently, less likely to ever enroll in a transfer-level English course. Similarly, Clotfelter et al. (2015), using an instrumental variables strategy relying on variation of placement policies and geographic proximity of various community colleges, find that students at the bottom of the 8th-grade achievement distribution are the most adversely affected by remediation.

A potential reason for these mixed outcomes stems from how students are defined as underprepared and placed into remedial education. For many years, a large proportion of community colleges across the nation relied solely on placement exam score cutoffs to place students into remedial education (Zachry Rutschow et al., 2019), and this was largely true in California community colleges (Cuellar Meija et al., 2016a). However, studies have shown that standardized testing routinely underplaces students into remedial education at an overwhelming rate (Belfield and Crosta, 2012), and can be a worse predictor of future academic success than overall high school performance (Scott-Clayton, 2012; Scott-Clayton et al., 2014; Allensworth and Clark, 2020).[8]

Initially, placement of students into remedial education varied widely across the 114 community colleges in California. Although the vast majority of colleges relied mostly on assessment test scores taken by incoming first-time students, there was substantial variation in the cutoff score used to place students into remedial education, and as well as the exam administered (Cuellar Meija et al., 2016b).

[7] For example, students who only required one remedial course faced the largest negative effects, and were less likely to complete a college degree and accumulated fewer college credits over time. However, students required to take two remedial courses faced less negative effects, and in some cases, were even more likely to persist than similar students who were required to take only one remedial course.

[8] However, there are some papers which suggest that standardized exams are just as good at predicting academic success as high school measures, or that standardized exams in conjunction with high school measures are better at predicting academic success.

These studies prompted the State legislature of California to pass a mandate in 2013 requiring community colleges to use multiple measures,[9] such as high school courses taken or GPA, to place students into remedial education, instead of relying so heavily on entrance exam scores.[10] However, studies of these early efforts suggested that multiple measures were being inconsistently applied across colleges, and that this uneven implementation resulted in slow-moving changes in remedial education participation (Cuellar Meija et al., 2016a). A large proportion of students were still enrolled in remedial education, with roughly 31 percent of students took a remedial education course during their first semester of enrollment.[11]

Concurrently, there was a related push in the California Community College system encouraging students to increase their transfer-level course participation, and thus encourage long-run student success.[12] Together, these changes indicate that transfer-level course participation should increase, and that remedial education enrollment should decrease during 2013-2017. However, descriptive studies indicated that these policies were not working quickly enough. To help further address these issues, California implemented one of the most sweeping changes to remedial education placement. In October 2017, AB 705 was passed, to address the well-documented problems regarding remedial education, and to change how colleges could place students into remedial education.[13]

AB 705 again reiterated that colleges more consistently use high school transcript data to place students, as research has shown standardized tests are poor indicators of future college success, and other measures, such as high school GPA, grades, and courses, can be better predictors of academic success (Scott-Clayton, 2012; Scott-Clayton et al., 2014; Allensworth and Clark, 2020). Furthermore, colleges had to "maximize the probability that a student will enter and complete transfer-level coursework in En-

[9] 5 CA ADC § 55522

[10] Other measures include grade in the last math/English course, high school GPA, the Early Assessment Program (EAP) or counselor recommendation.

[11] Statistics calculated internally.

[12] The California Community Colleges Chancellor's Office has made a concentrated push to improve student outcomes, specifically through closing achievement gaps, increasing degree attainment and transfers to four-year universities, and reducing unnecessary credit accumulation. *See,* Vision for Success. California Community Colleges. *https://www.cccco.edu/About-Us/Vision-for-Success*. Accessed 07 Jan. 2022.

[13] AB 705 Resources. Academic Senate for California Community Colleges. https://asccc.org/ab-705-resources. Accessed 24 March 2021.

glish and math within a one-year timeframe,”[14] suggesting that enrollment in remedial education would no longer be the default for entering students. These factors together suggest that it will be difficult for colleges to deny most students entry to transfer-level courses. AB 705 mandated that these changes be implemented systemwide by Fall 2019, although some colleges chose to pilot these changes earlier in 2018.[15]

A priori, it is not certain what effects these policy changes will have on student outcomes. Increasing direct access to transfer-level courses necessary for degree attainment or transferring to a 4-year college could decrease time to degree by allowing students to take the necessary classes more quickly. On the other hand, if some students really are underprepared, then allowing direct access to transfer-level courses could result in more attrition and lower pass rates than before the policy change.

Few papers assess the impact of increasing open access to transfer-level courses, with the notable exception of recent studies focused on Florida. In 2014, Florida passed a similar bill to AB 705, drastically restructuring remedial education in the Florida College System, and no longer requiring students take the remedial education placement exam.[16] Park-Gaghan et al. (2020) find that the effective removal of remedial education helped narrow achievement gaps in gateway course passing for underrepresented minorities. Park-Gaghan et al. (2021) also find positive effects on course pass rates for all students across different levels of college preparedness, as defined by general high school course taking, with the largest effects for students deemed the least prepared. However, they are unable to fully account for any linear pre-trends in their analysis, and cannot disentangle effects of policies that potentially affect students at all levels of academic preparation similarly. I add to the literature on increased direct access to transfer-level courses by studying students along a continuous measure of college readiness, instead of focusing on students at the margin. Furthermore, I have a rich set of rarely available controls to account for student ability, through standardized tests in both English and math taken in high school.

[14] California State Assembly Bill. Assembly Bill 705: Seymour-Campbell Student Success Act of 2012. SEC 2.78213d(1)(A).

[15] The RP Group (2019). “Access, Enrollment, and Success in Transfer-Level English and Math in the California Community College System.” https://mk0edsource0y23p672y.kinstacdn.com/wp-content/uploads/2019/09/AccessEnrollmentSuccess_FINAL.pdf. Accessed May 5, 2021.

[16] SB 1720. https://www.flsenate.gov/Committees/billsummaries/2013/html/501.

3 Data

For this analysis, I use administrative data on the California Community College (CCC) system, which encompasses 116 colleges and represents the largest public higher-education system in the United States, serving over 2.1 million students.[17] This administrative data from the California Community Colleges Chancellor's Office (CCCCO) includes the population of students who enrolled in a community college from 2000-2020, although I focus only on college enrollment from 2011-2020 due to the timing of the policy change and other data restrictions.

The CCCCO data include information on the individual student's demographics, such as gender and race, as well as comprehensive transcript data. The transcript data are at the student-term level, and includes information on all courses taken by an individual student, including the grade earned in each course, the total number of units attempted, units earned, as well as longer-run outcomes, including certificates, awards earned, and transfer status. The CCCCO data also include granular data on each course, including remediation (or basic skills) status and subject, as well as transfer status.

I complement the CCCCO data by matching at the student level to data on the entire universe of public high school students in California. This data from the California Department of Education (CDE) cover 5.7 million students from 2008 - 2020, with an average of 475,000 students per cohort. In addition, the CDE data include demographic information on the student's gender, race, socioeconomic status, birthday, and high school attended.

4 Empirical Strategy

I use the introduction of various remedial education reforms in 2013, as well as the removal of mandatory remedial education in 2017, as sources of quasi-exogenous variation to study how changes in access

[17] Facts and Figures. Foundation for California Community Colleges. https://foundationccc.org/About-Us/About-the-Colleges/Facts-and-Figures. Accessed May 5, 2021.

to transfer-level courses affect students' academic success at California community colleges, measured by course selection, pass rates in transfer-level courses, and overall course load. I compare college outcomes of students, before, during, and after the policy changes. I define the "before" period to be from Fall 2011 up to and including Spring 2013, the "intermediate" period to start from Fall 2014 up to and including Fall 2017, and the "after" period to be from Spring 2017 to Spring 2020.

Importantly, I do not observe whether students are recommended to enroll remedial education, only if they actually enroll in a remedial education course. Thus, I am not able to observe which students may have initially been recommended to take remedial courses, but did not actually take those courses due to exam retakes, or dropped out of school before taking remedial courses. Furthermore, as students no longer have to take the entrance exam that places students into remedial education after the implementation of AB 705, it's difficult to say which students might be affected by these remedial education reforms.

Instead, I use a rich variety of variables on demographics and ability chosen through a data-driven process to *predict* treatment intensity – a continuous variable representing the predicted probability a student takes remedial English (and separately for math) within the first semester of enrollment. Specifically, I focus on the first semester within the first year of enrollment conditional on the student being enrolled in credit-bearing courses. This restriction allows me to avoid any biases regarding students persisting into the spring semester, or students whose first semester is in the spring rather than the fall.[18]

I use the predicted probability of enrolling in a remediation course as a proxy for counterfactual treatment intensity had remedial education reforms not been passed to estimate the following equation:

$$\begin{aligned} Y_{ihcts} = \alpha + \beta_1[\text{intermediate}_t] + \beta_2[\text{after}_t] + \beta_3[\hat{\mathrm{T}}_{ihc(s=math)}] + \beta_4[\hat{\mathrm{T}}_{ihc(s=Eng)}] \\ + X_{ihc} + \lambda_c + \lambda_h + \epsilon_{ichts} \end{aligned} \tag{1}$$

[18] 23 percent of students first enroll in community college in the spring semester rather than the fall semester.

where each observation is unique at the student i-semester t level, and Y_{ihcts} represents both continuous and binary outcomes, such as the total number of units taken in a semester or whether or not a student passed a transfer-level course for subject s (English or math). The variable $intermediate_t$ is an indicator variable which is 1 if the student is enrolled in community college during the initial reform period, when the course selection reforms focused on students with higher levels of academic preparation, during Fall 2014 to Fall 2016, inclusive. The variable $after_t$ is an indicator variable which is 1 if the student is enrolled in community college after the passing of AB 705, during Spring 2017-Spring 2020, inclusive. Finally, $\hat{\mathrm{T}}_{ihcs}$ is the predicted treatment intensity, and is a continuous measure ranging from 0 to 1. The larger $\hat{\mathrm{T}}_{ihcs}$, the more likely a student is predicted to have enrolled in a remedial education course in subject s within the first semester of enrollment. I control for both the predicted treatment intensity for English ($s = Eng.$) and math ($s = math$).

The coefficient of interests are β_1 and β_2, and fixed effects λ_c and λ_h are estimated at the college and high school level. X_{ict} is a vector of controls, including a linear time trend, and student controls for gender, race, age (in months), socioeconomic disadvantage status, and 6th grade standardized test scores in both ELA and math.

4.1 Model Selection and Predicted Treatment Intensity

To model predicted treatment intensity, I fit a lasso-logistic model to identify the best factors to predict the probability that a student would have enrolled in remedial education before the passing of remedial education reforms without overfitting the model.[19] I use characteristics chosen from the CDE dataset to estimate a logit model calculating the probability a student would have been placed in remedial education,

[19] The lasso logit methodology is a method of choosing variables to improve the prediction accuracy of a model, and in particular works to minimize the following equation:

$$L + \lambda(\sum |\beta_1| + |\beta_2|) + |\beta_3|) + ... \tag{2}$$

where L represents the log likelihood function, but the parameter of importance is λ, the penalization parameter. Various methods can be used to choose this parameter, but I use adaptive lasso, which is typically used when the goal is model selection. This particular method typically yields fewer variables than other methods.

had these reforms not been passed.[20]

Important variables included in the lasso choice set are standardized test scores in both English and math; however, because California switched from the CST standardized test to the SBAC standardized test in 2014, and the two tests are not comparable over time, I use 6th grade test scores, which are the most recent test scores such that all students in the sample take the same version (CST).[21]

For this analysis, I focus specifically on students who decide to enroll in community college immediately after high school. This sample restriction is also partially due to data limitations after the implementation of AB 705 in 2017.[22] This constraint ensures that students in the later cohorts have an equal opportunity to enroll in community college as students who graduated high school earlier. Furthermore, depending on the timing of enrollment, these remedial education reforms might be more or less salient, depending on the student's goals. For example, "traditional" students' goals lean more towards 4-year transfer and degree receipt compared to students who might be enrolling in community college after spending time in the labor force thus making AB 705 more salient for their course selection.[23]

To find the predicted treatment intensity variables, I regress actual remedial education status on a host of characteristics chosen using the lasso logit methodology, a purely data-driven process that does not rely on a theoretical basis for choosing variables for prediction. This allows me to be agnostic as to why certain variables should or should not predict remedial education status.

I fit separate models for both predicted English and math remediation during the first semester of enrollment. I use only students who enroll in community college during 2011-2013, before any reforms to remedial education or course selection occurred, to create my prediction model. Furthermore, I focus on students who enroll in at least one credit-bearing course.[24]

[20] The complete list of the CDE variable choice set is in Figure 7 in the Appendix.

[21] A potential robustness check could be to use only students with SBAC scores. However, this would exclude cohorts before 2013, who are the control group necessary for the analysis.

[22] This restriction is also due to being in between two different standardized test regimes.

[23] Findings from Calcagno and Long (2008) support the idea that remediation might have positive effects for nontraditional students, in contrast to the somewhat negative effects of remediation on traditional students.

[24] Both transfer-level and remedial courses are credit-bearing, but remedial courses do not count towards a degree.

To predict whether a student would have enrolled in a remedial course within the first semester of enrollment, I estimate separate binary logit models using the model chosen by the adaptive lasso method for each subject. These predictions are then included in Equation 1 as $\hat{\mathrm{T}}_{ihcs}$, as a continuous measure of treatment intensity, and represent the perceived college readiness of the student had the student been enrolled in community college during the period before any policy change.[25]

Comparing the kernel densities of predicted probability of enrolling in remedial English for students in community college before, during, and after remedial education policy changes, there are fewer students with lower predicted probabilities of remedial English enrollment in community college during the "before" period, compared to students in the "intermediate" period and "after" period. Similarly, there are slightly fewer students with lower predicted probabilities of remedial English enrollment in the intermediate period compared to the after period. However, with respect to students with higher predicted probabilities of remedial English enrollment, the densities across time periods seem similar. The distribution of the predicted probability of remedial English enrollment is statistically significantly different across time periods. There is a larger difference in the distribution of the predicted probabilities of math remedial enrollment compared to the distribution of the predicted probabilities of English remedial enrollment. Again, students in the period after the policy change are more likely to have a lower predicted probability of enrolling in remedial math than students in the period before and during remedial education policy changes.

5 Summary Statistics and Descriptive Trends

To understand how these policies may have affected community college students' course selection, I graph course participation trends, separately by English and math course participation. Figure 1a graphs the proportion of students enrolling in each type of English course. I define "on-time" to be students who enrolled in community college during the first year after high school graduation. I focus on the student's

[25] Table A1 in the Appendix displays the selected model and associated coefficients for predicting English remedial participation and math remedial participation for students during the first semester a student is enrolled, respectively.

first semester of attendance during this first year. Although the focus of this paper is on transfer-level and remedial course participation, I include participation in the non-transferable, degree-credit courses, such that the graph represents all English course takers.[26]

Course participation rates in both transfer-level and remedial English are relatively flat from 2011-2013. After the implementation of the multiple measures mandate in 2013, represented by the red dashed line, there is a steady increase in transfer-level course taking, as well as a slight decrease in remedial English course taking. By 2017, after AB 705 (represented by the solid red line), there are larger increases in transfer-level English course participation, and decreases in remedial English course taking. There are similar, although somewhat muted, patterns regarding math course participation rates, as shown in Figure 1b.

5.1 Composition Changes

It is possible that the changes in course participation rates as seen in Figure 1a and Figure 1b are not a result of policy changes, but rather changes in composition of the students enrolling in community college during each time period. For example, if more students with higher abilities who could directly enroll in transfer-level courses regardless of any policy reforms decided to attend community college, then this could also explain the observed increases in the proportion of students taking transfer-level courses over time.

The average predicted probability of requiring remedial English for students enrolled in community college is similar across the three time periods, with a slightly lower likelihood of 0.005 percentage points for students after 2017. A similar pattern regarding the predicted probability of remedial math enrollment is seen across these three time periods as well.[27] Next, I disaggregate these summary statistics to focus on how these demographic characteristics trend over time, and whether these trends move smoothly over

[26] There are also non-degree credit, non-remedial courses, but the proportion of students enrolled in those courses are relatively stable and close to 0 across all years. Graphs including those trends are included in the Appendix.

[27] Table A2 in the Appendix presents summary statistics on the average demographic characteristics over the entire period of analysis, along with summary statistics within each time period, before, during, and after the policy changes of interest.

time. It might be concerning if there are large discrete changes in student composition at the same time as the policy changes, which could potentially be the true driver of effects observed, instead of the policy changes. However, this does not seem to be the case,[28] suggesting that any shifts in demographic composition are not driven by changes in selection by students enrolling in community college.

To further investigate whether the observed changes in course participation could stem from a change in the combination of demographic and ability variables, I predict the probability of enrolling in a transfer-level English or math course. I use various demographic variables, such as race, gender, socioeconomic status, and ELA and math standardized test scores to predict transfer-level course taking in either English and math for students enrolled in community college in the period before any policy change. I then use that prediction model to estimate the proportion of students likely to take transfer-level courses based on these variables alone. If changes in these demographic and ability variables are actually the reason behind the observed course selection changes, then these predictions would project a similar trend as the observed course selection changes.

I graph the average likelihood of taking a transfer-level course by year, along with the actual proportion of students taking a transfer-level course. As Figure 2a and Figure 2b show, the predicted proportion of students enrolled in transfer-level courses based on demographic and ability characteristics alone is very stable and flat across all time periods, relative to the actual proportion of students enrolled in transfer-level courses.

These graphs provide evidence that changes in transfer-level course participation in either English or math do not stem from composition changes in the students deciding to enroll in community college across time, and instead are likely driven by changes in policy.

[28] Figures Figure A2a, Figure A2b, and Figure A3 in the Appendix show that, although there might be changes in demographic composition or average standardized text scores, these changes are smooth across the vertical lines representing the year of policy reform, suggesting that these changes are not driving any changes in outcomes observed. Figure A2b also indicates that these changes are merely reflective of overall demographic shifts of public high school students in the state of California, not just those students entering community college.

6 Results

I investigate how students are affected by the two sets of policy changes. The first policy change consisted of the multiple measures mandate implemented in 2013. As hypothesized earlier, this measure is likely to affect students who had higher levels of academic preparation most. In contrast, AB 705 with its effective removal of remedial education requirements is likely to affect the students with the lowest level of academic preparation most.

6.1 Overall

I first examine how these two bundles of policies affected all students on average. Table 1 displays the average treatment effects of each policy period. The "Pass with a C" outcome is a binary measure, and equals 1 if a student received a C or better in a transfer-level course in English or math respectively, and 0 if otherwise. As many students might not elect to enroll in transfer-level courses, I assign those students a 0, and thus capture the intent-to-treat (ITT) effect of the policies.

"Intermediate" represents the initial period of policy reform from Fall 2014 - Fall 2017, covering the multiple measures mandate. Following this mandate, remedial English (math) enrollment increases 1.6 (2.4) percentage points, while transfer-level English enrollment increases 11 (4,4) percentage points, and the probability of passing transfer-level English (math) with a C or better increases by 9.7 (3.6) percentage points. The treatment-on-the-treated effect (TOT) is 88.2 (81.8) percent, suggesting that, conditional on enrolling in an English (math) transfer-level course, 88.2 (81.8) percent of those students passed with a C or better. This is considerably higher than the transfer-level English (math) pass rate during the period before any policy was implemented, at 77.22 (69) percent.

There are significantly larger effects on course selection for students enrolled in the "after" period (i.e. after the implementation of AB 705 in Fall 2017). There is a large decline in the proportion of students enrolling in remedial English after AB 705, suggesting that the policy did have the intended effect. There is a comparatively larger effect on transfer-level English (math) enrollment, at 31 (16.1) percentage points, with a corresponding increase in the probability of passing transfer English (math) of 26.5 (11.2) percentage points. This translates to a TOT effect of 85.48 (69.5) percent, which again is higher than the transfer-level English (math) pass rate of 77.22 (69) percent before any course selection policy was implemented. If we assume the influx of students enrolling in transfer-level English (math) were indeed all students who would have been placed in remedial education in the regime before AB 705 was implemented, then 85 (69.5) percent of them could have passed transfer-level English (math) had they not been recommended to take remedial English (math).

Finally, I look at how these policies affected overall course load for students. I find that the number of both overall units, which include remedial courses in its count, and transfer-level units earned and attempted increased across both time periods. That the increase in overall units is smaller than the increase in transfer-level units, but still positive, suggests that although some students fully substituted remedial courses for transfer-level courses, some might have attempted other additional transfer-level courses, and thus attempting more units overall.

I find that that overall course completion rates were larger in the intermediate period (51 percent) than the "after" period (28.7 percent), but both overall course completion rates were lower than the before policy overall course completion rate of 73.5 percent. However, these overall course completion rate comparisons might be somewhat misleading, as students could be substituting remedial education courses for transfer-level courses in a multitude of ways. In contrast, the transfer-level course completion rate during the intermediate period of policy reform of 84.1 percent is actually higher than the analogous completion rate of 75 percent before any policy change, as well as the transfer-level completion rate of students after AB 705 passed at 66.5 percent. This result suggests that after AB 705 was passed, students might have been attempting more transfer-level units than they could handle.

Taking these results together, there are two noticeable patterns. First, that relative to English course-taking results, there are much smaller effects on math course-taking. Anecdotal evidence indicates that students are more hesitant to take transfer-level math courses[29] and that advisors are likely to suggest below transfer-level math placement for students with lower levels of college readiness (Cuellar Meija et al., 2021).

Second, TOT effects on transfer-level pass rates, as well as transfer-level course completion rates, tend to be higher during the intermediate period of reform when the multiple measures mandate was implemented, compared to the TOT effects for students after AB 705 was passed. This points to suggestive evidence that each set of policies affect students at opposite ends of the college readiness scale. In other words, the remedial education placement reforms affects students on the margin of requiring remedial education, or with higher levels of academic preparation, while AB 705 affects students with lower levels of academic preparation. In order to test this hypothesis rigorously, I next conduct a heterogeneity analysis, grouping students by their predicted probability of enrolling in a remedial course, a proxy for perceived college readiness.

6.2 Heterogeneity Analysis

To conduct the heterogeneity analysis, I split the sample into four quartiles, based on students' predicted probability of enrolling in remedial education (predicted treatment intensity), separately for English and math. Students in the first quartile are those who are deemed the more academically prepared, and students in the fourth quartile are those who are deemed less academically prepared, as under the old remedial education system before any policy change, which focused on standardized exams scores as cutoffs.

[29]"Overcoming Math Anxiety." Mission College Santa Clara. *https://missioncollege.edu/depts/math/math-anxiety.html.* Accessed 07 Jan 2022.

6.2.1 Course Taking

I first graph the proportion of students within each predicted probability quartile enrolled in remedial English and math, respectively, in Figure 3a and Figure 3b. The red dashed line represents when the multiple measures mandate was implemented in 2013, and the red solid line represents when AB 705 was implemented in 2017. As expected, the largest declines in remedial participation after AB 705 was passed are concentrated among students in the 3rd and 4th quartiles, or the quartiles of students deemed the least college ready.

Similarly, Figure 4a and Figure 4b graph transfer-level course participation in both English and math by quartile, respectively. For both English and math, there is a steady increase in transfer-level course participation during the intermediate period of policy change. In contrast, after AB 705 was passed, while there are increases in transfer-level participation at steeper rates for students in the 2nd and 3rd quartile than for students in the first quartile, the sharpest increase observed is for students in the 4th quartile, or students deemed least prepared for college.[30] There is not, however, a similar pattern observed for math transfer-level participation by quartile; although there are increases in transfer-level participation across all quartiles, the largest participation rate increase is not concentrated among students in the 4th quartile.[31]

Table 2 shows how each quartile of students were affected by the policy changes. After AB 705 was implemented, the overall decline in remedial English participation as observed in Table 1 is driven by large declines in English remedial participation by students in the 3rd and 4th quartiles, or the students who are deemed the least academically prepared. Furthermore, it is students in the 4th quartile, who are 23 percentage points less likely to be enrolled in English remediation.

The increase in transfer-level participation increases at a decreasing rate across quartiles, for students enrolled in the intermediate period, while the opposite pattern is observed for transfer-level participation

[30]The observed increase in transfer-level English course participation rates after the implementation of AB 705 were 0.040, 0.098, 0.122, and 0.221, for quartiles 1, 2, 3, and 4, respectively.

[31]In contrast, the observed increase in transfer-level math course participation rates after the implementation of AB 705 were 0.07, 0.116, 0.125, and 0.08, for quartiles 1, 2, 3, and 4, respectively.

during the period AB 705 was passed, with students in the 4th quartile experiencing the largest increase in transfer-level English participation. These patterns support the hypothesis that the multiple measures mandated implemented during the intermediate policy period affected more students who were more academically prepared, and AB 705 affected more strongly students who were deemed less academically prepared.

For the intermediate policy period, the increase in the probability of passing transfer-level English is positive across all four quartiles of students, but declines moving from students with the highest level of academic preparation in the 1st quartile to students with the lowest level of academic preparation in the 4th quartile. In contrast, after AB 705 was passed, the observed pattern is reversed, with students in the 4th quartile experiencing the largest increase in the probability of passing transfer-level English with a C or better, at 28.4 percentage points.

When looking across all four quartiles, the pass rate conditional on actually taking a transfer-level English course (TOT effect) is higher for students enrolled in the "intermediate" period than the "before" period. This pattern is similar for students enrolled in the period after AB 705 was passed, except for students in the fourth quartile, or students deemed the least college prepared, with respect to the old remedial education placement system. This finding suggests that some of the students in the fourth quartile who enrolled in transfer-level English might not yet have been prepared to take that course.

Table 3 shows the same analysis for math course taking. Overall, there are similar, though more muted patterns observed for math course taking. However, with respect to transfer-level math participation after AB 705 was passed, the increase in participation rates is no longer increasing across quartiles. Although the changes in enrollment are positive across all quartiles, the changes are relatively similar across the 1st, 2nd, and 3rd quartiles, with a slightly smaller increase for students in the 4th quartile. In fact, the increase in transfer-level math enrollment for students in the 4th quartile does not offset the decrease in remedial math participation, suggesting that despite open access, students who are deemed least ready for college math are the most hesitant to enroll in transfer-level math.

There are also increases in the proportion of students passing transfer-level math with a C better across all quartiles and across both time periods. Unlike English transfer-level pass rates in the period after AB 705 was passed, math transfer-level pass rates follow a similar pattern as math transfer-level pass rates for students enrolled in the intermediate period.

6.2.2 Course Load

Another outcome of interest is overall course load. Although course selection policies directly affected remedial and transfer-level English and math courses, it is possible that students shifted their other course taking as well. Students might opt to take fewer courses overall as a response to taking more time-intensive, difficult transfer-level courses. On the other hand, students who no longer have to enroll in remedial courses might substitute to transfer-level courses instead, and may even be encouraged to take additional transfer-level courses.

Focusing on changes in overall transfer-level units taken by English readiness quartiles,[32] I find that there are increases in both transfer-level units attempted and earned across both time periods, and across all quartiles, as seen in Table 4.

However, it is uncertain if these results are merely reflective of the increases in English transfer-level course taking. If students in the 4th quartile experienced a 37 percentage point increase in the probability of enrolling in transfer-level English, then a 1.11 unit increase in overall attempted transfer-level course taking is expected for students in the 4th quartile.[33] In contrast, students are, on average, enrolling in an additional 2.75 transfer-level units, suggesting that, in addition to enrolling in transfer-level English, students in the 4th quartile are also attempting other transfer-level courses.

Potentially more informative are transfer-level course completion rates, which I calculate by dividing

[32] I conduct a similar analysis for math transfer-level units. However, results are largely similar, due to the fact that students in a particular quartile based on predicted English remedial enrollment is likely in the same quartile based on predicted math remedial enrollment. Tables are located in the Appendix.

[33] On average, a course is 3 units. 0.37 * 3 = 1.11

the increase in transfer-level units earned by the increase in transfer-level units attempted. The transfer-level course completion rate by students enrolled during the intermediate policy period are, across all quartiles and overall, higher than that of students enrolled before the course-selection policies of interest. In contrast, there are much lower transfer-level course completion rates for all quartiles of students enrolled in community college after the implementation of AB 705, compared to both students enrolled in community college during the intermediate period of policy reform and students enrolled before any reform.

That the coefficients for overall units (not just transfer-level) in Table 5 are positive, but not as large as increases in transfer-level units taken suggest that while some students are substituting their remedial course for a transfer-level course, some students are also taking *additional* transfer-level courses. That is, if students were only substituting remedial courses and transfer-level courses, then there should be no changes in overall course load.

I find that, overall, there were increases in the proportion of students across all levels of college readiness who enrolled and passed transfer-level English and math with a C or better, after the introduction of AB 705, despite mostly affecting students deemed less academically prepared for college. When examining the TOT effect, I find that almost all students across a range of college readiness were able to pass transfer-level English (and math) courses at similar, or higher, rates than students enrolled in community college before either set of policy changes. This does not hold, however, for students in the 4th quartile of either the predicted probability of enrolling in English and math. This result suggests that some students who are the least prepared that are enrolling in transfer-level English or math that may not be ready to do so.

6.3 By Treatment Intensity

Finally, I use the predicted probability of enrolling in remedial English (math) as a continuous treatment variable, and interact it with the "intermediate" and "after" policy variables, estimating the following equation:

$$
\begin{aligned}
Y_{ihcts} = \alpha &+ \beta_1[\text{intermediate}_t * \hat{\text{T}}_{ihcs}] + \beta_2[\text{after}_t * \hat{\text{T}}_{ihcs}] \\
&+ \beta_3[\text{intermediate}_t] + \beta_4[\text{after}_t] + \beta_5[\hat{\text{T}}_{ihcs}] \\
&+ \lambda_c + \lambda_h + X_{ihc} + \epsilon_{ichts}
\end{aligned} \tag{3}
$$

where each observation is unique at the student i-semester t level, and Y_{icts} represents both continuous and binary outcomes, such as the total number of units taken in a semester or whether or not a student passed a transfer-level course for subject s (English or math). The variable $intermediate_t$ is an indicator variable which is 1 if the student is enrolled in community college during the initial remedial education reform period, where reforms centered on the method of remedial education placement, during 2013-2017. The variable $after_t$ is an indicator variable which is 1 if the student is enrolled in community college after the passing of AB 705, during 2018-2019. Finally, $\hat{\text{T}}_{ics}$ is the predicted treatment intensity, and is a continuous measure ranging from 0 to 1. The larger $\hat{\text{T}}_{ics}$, the more likely a student is predicted to have enrolled in a remedial education course in subject s within the first year of enrollment.

The coefficients of interests are β_1 and β_2, and fixed effects λ_c and λ_h are estimated at the college and high school level. X_{ihc} is a vector of controls, including a linear time trend, and student controls for gender, race, age (in months), socioeconomic disadvantage status, and 6th grade standardized test scores in both ELA and math.

The purpose of this exercise is to try and isolate the effects of AB 705 as a policy on its own. Considering the suggestive evidence that AB 705 had disparate effects on students with the highest predicted probability of enrolling in remedial education, and should have not affected students with the highest academic preparation (or the lowest predicted probability of remedial education enrollment) as much. The expectation would be to see effects increase as the predicted probability of remedial enrollment increased.

Table 6 looks at these effects treating college readiness as a continuous variable. Looking at effects during the "intermediate" policy period, there is no longer a statistically significant change in the proportion of students taking remedial English as the predicted treatment intensity increases.[34] There are statistically significant decreases in both transfer-level English course taking and the corresponding pass rate, corresponding to that in Table 2, all quartiles of students experience large increases in English transfer-level participation, but at a decreasing rate. It is reassuring that the decrease in passing with a C or better is almost exactly the same as the decrease in transfer-level English participation, suggesting that the decrease in pass rate is a result of the decrease in course participation.

Focusing on students after AB 705 was passed, there are large reductions in enrolling in remedial English and math that increase as the predicted probability of remedial enrollment increases. A one standard deviation increase of 16 percent in the predicted probability of enrolling in remedial English leads to a 9.9 percent decrease in the probability of actually enrolling in remedial English, and a 4.7 percent increase in the probability of enrolling in transfer-level English. A one-standard-deviation ITT effect on the transfer-level English pass rate is 2 percent. That the increase in transfer-level English participation is smaller than the decrease in remedial English participation suggests that as the predicted probability of remedial English enrollment increases (i.e., as students are more likely underprepared for school), students are more hesitant to take transfer-level English.

Again, there are similar patterns for math course taking, although all effects are smaller than that for English course taking. Although there are statistically significant reductions in both the transfer-level math enrollment and corresponding pass rate as the predicted probability of math remedial enrollment increases, the declines are exactly the same, suggesting that the decrease in pass rate is driven only by decreases in transfer-level math enrollment.

After AB 705, a one standard deviation increase in the predicted probability of enrolling in remedial math of 16 percent leads to a 8.8 percent decline in the probability of actually enrolling in remedial math.

[34] In Table 2 the increases in remedial English participation are not increasing when moving from the 1st quartile to the 4th quartile.

However, interesting to note is that there is no longer a statistically significant increase in the proportion of students enrolling in transfer-level math *as the predicted probability of enrolling in remedial math increases.* Note in Table 3 that while there were positive effects of AB 705 on the proportion of students enrolling in transfer-level math for students in all quartiles, those increases slightly decreased moving from the 1st quartile to the 4th. Initially disappointing is seeing that the intent-to-treat effect of AB 705 is negative for passing transfer-level math with a C or better. However, in light of the quartile analysis in Table 3, this negative coefficient indicates that there are still increases in the probability of passing transfer-level math, but that these increases are decreasing as the probability of requiring remedial math increases.

These results make intuitive sense – students who seem less prepared are more hesitant to enroll in transfer-level courses despite open access. This can be seen from the fact that the decrease in remedial course enrollment was not completely offset by the increase in transfer-level enrollment. Furthermore, the declines in math transfer-level pass rates indicate that pass rates declined as students who were deemed less college prepared enrolled in transfer-level math.

These results do not contradict the heterogeneity analysis by quartile. This treatment intensity analysis hypothesizes that effects from these policies change at an increasing rate along a continuous measure of college readiness. That is, it is not enough for there to be a level shift across all students, but that students with the highest predicted probability also experience the largest change.

Next, Table 7 shows how overall course load changed during the different policy periods, for students as they are deemed less and less prepared for college. Although overall units attempted did not increase during either policy, the number of units earned does decline after AB 705 was introduced, with the number of units earned declining as students are deemed less and less prepared for college. However, these seemingly negative effects hide changes in the *types* of courses being taken.

After AB 705 was passed, a one standard deviation increase in the predicted probability of enrolling in remedial English of 16 percent leads to a 0.32 increase in the number of transfer-level credits attempted, and a 0.09 increase in the number of transfer-level credits earned.[35] These results together suggest that students who were most affected by AB 705, that is students who were deemed the least prepared for college, were likely substituting some of their remedial courses with transfer-level courses, but not all, leading to an overall decline in units taken, but an increase in transfer-level courses taken. Observing these treatment intensity results in conjunction with the quartile results indicates that while students at all levels of college readiness experienced positive results as a result of the reforms, these benefits declined as students' academic preparation decreased.

7 Conclusion

Remedial education is a costly practice implemented across the United States to address the flagging academic success of students deemed underprepared for college work. However, despite the widespread use of remedial education, previous empirical studies have found mixed results regarding its effect on students' academic success, and it is uncertain how a policy increasing open access to transfer-level courses for all students might affect the academic success of students.

I add to this literature by being the first to study the effects of remedial education reform policies for students on a continuous measure of college readiness, and for the state of California. In particular, I find that the multiple measures mandate passed in 2013 had smaller effects on course selection than did AB 705 passed in 2017. However, while the multiple measures mandate targeted students with more academic preparation, AB 705 influenced more students at lower levels of college readiness.

After increasing direct access to transfer-level courses, there were large increases in transfer-level participation, and pass rates, in both English and math, suggesting that many students who would have been placed in remedial courses could have passed transfer-level courses at similar or higher rates than students before any policy was passed. This result is true for all students except for students with the lowest level

[35] Results are very similar using the likelihood of requiring remedial math.

of academic preparation. Although these students still experienced increases in the likelihood of passing transfer-level English and math, the conditional pass rate was lower than the pass rate before any course selection policies were passed. This suggests that some students with lower academic preparation were taking transfer-level courses before they were adequately prepared.

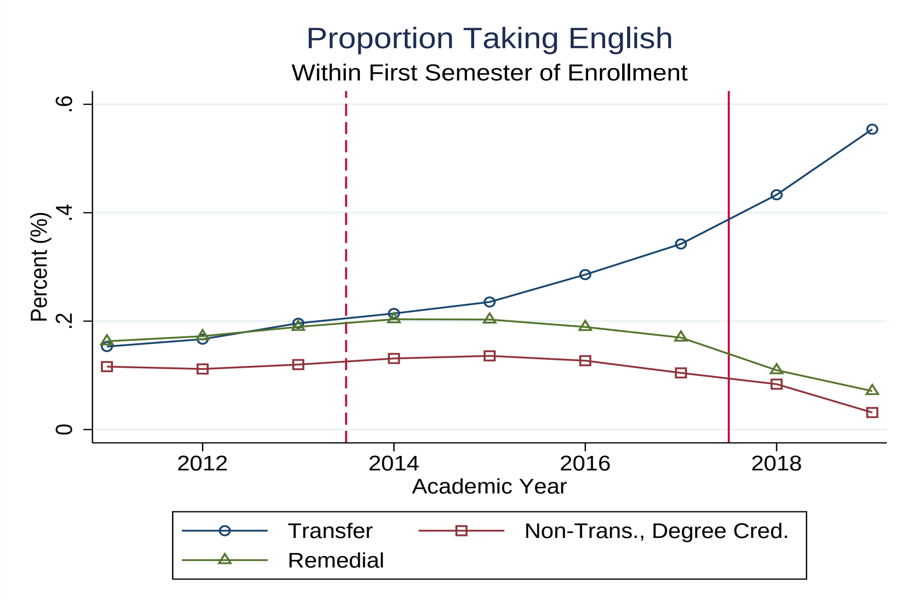
Furthermore, as college readiness declines, I find that students are more hesitant to take transfer-level courses, despite open access, particularly in math. Anecdotal evidence has suggested that could be driven in part by counselors' hesitance in encouraging students to take transfer-level math. This finding might be somewhat concerning, particularly in light of the importance of "gateway momentum," and evidence suggesting that students students who are able to take and complete transfer-level, or "gateway" math and English courses, within their first year of enrollment are more likely to graduate with college credential.[36] My results suggest that if a major goal of these remedial education reforms were to help encourage student success, there may be other barriers besides remedial education in place.

I also find that there were increases in transfer-level units attempted and earned. However, the course completion rate lower for students enrolled after AB 705 was implemented compared to students enrolled in the period before any policy change. These results suggest that although increasing direct access to transfer-level courses encourages students to take more transfer-level courses, the additional courses might be more than some students can handle.

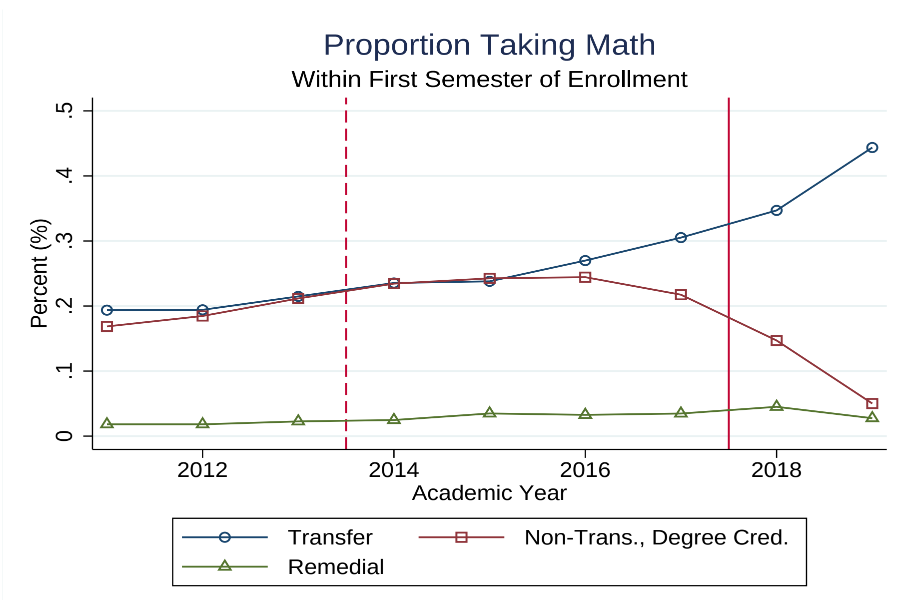
Overall, I find that these remedial education reform policies had a positive effect on transfer-level course participation and pass rates on students across all ranges of academic preparation, with the largest positive effects for students on the margin of requiring remedial education. A natural question to ask is, given these positive short-run effects, how might these policies affect long-run outcomes, such as transfer to a 4-year college, or receiving an associate degree, and the timeframe in which they complete these goals.

[36]Jenkins, Davis and Thomas Bailey. "Early Momentum Metrics: Why They Matter for College Improvement." CCRC. Feb. 2017. https://files.eric.ed.gov/fulltext/ED572783.pdf.

Figure 1: Observed Course Participation



(a) English Course Taking



(b) Math Course Taking

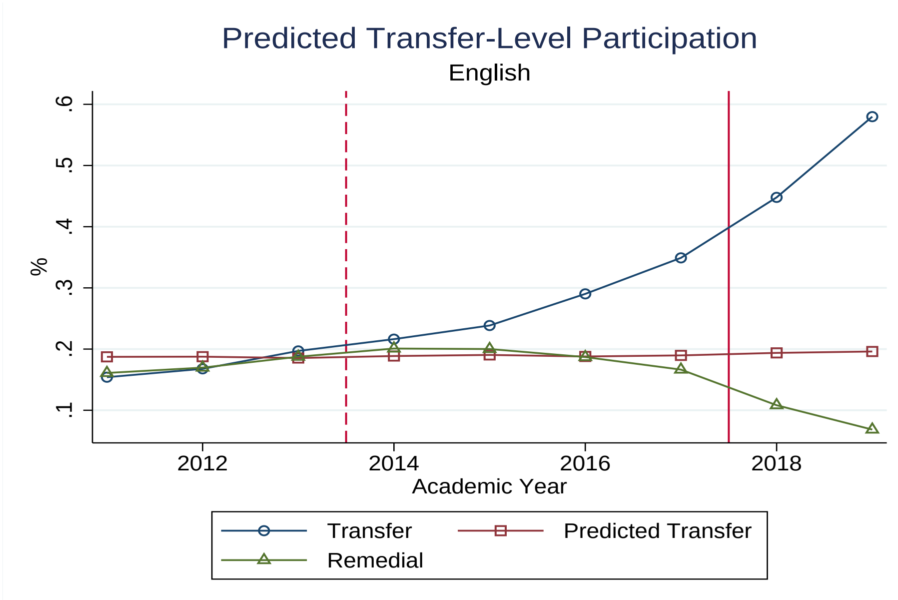
Notes: These two graphs show the observed proportion of students taking English or math courses throughout time. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

Table 1: Changes in Course-Taking

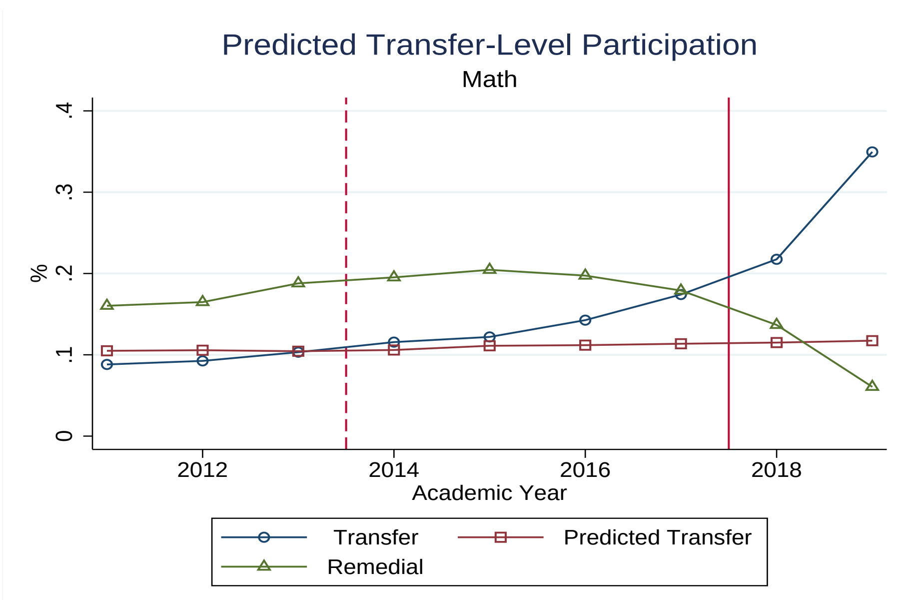
	Any	Remedial	Transfer-Level	Pass C
English Course Taking	(1)	(2)	(3)	(4)
Intermediate	0.127***	0.016**	0.110***	0.097***
	(0.010)	(0.007)	(0.007)	(0.006)
After	0.156***	-0.074***	0.310***	0.265***
	(0.014)	(0.012)	(0.014)	(0.010)
Average	0.472	0.173	0.180	0.139
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X
Predicted Treatment Intensity	X	X	X	X
Math Course Taking	(1)	(2)	(3)	(4)
Intermediate	0.100***	0.024***	0.044***	0.036***
	(0.009)	(0.005)	(0.004)	(0.003)
After	0.043***	-0.057***	0.161***	0.112***
	(0.012)	(0.010)	(0.010)	(0.007)
Average	0.455	0.170	0.102	0.071
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X
Predicted Treatment Intensity	X	X	X	X

Notes: For purposes of comparison, the "average" is calculated using only students enrolled in community college before any policy change (2011-2013). The outcome is a binary variable for whether or not the student took (a) any English/math course, (b) a remedial English/math course, (c) a transfer-level course, and (d) passed the transfer-level course with a C or higher. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Figure 2: Predicted Transfer-Level Course Participation



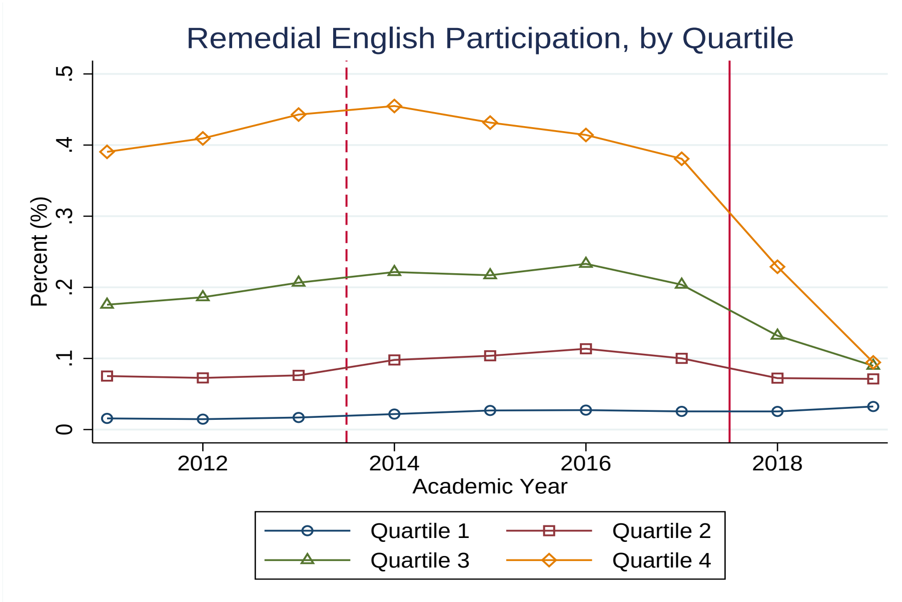
(a) Predicted English Transfer-Level Course Taking



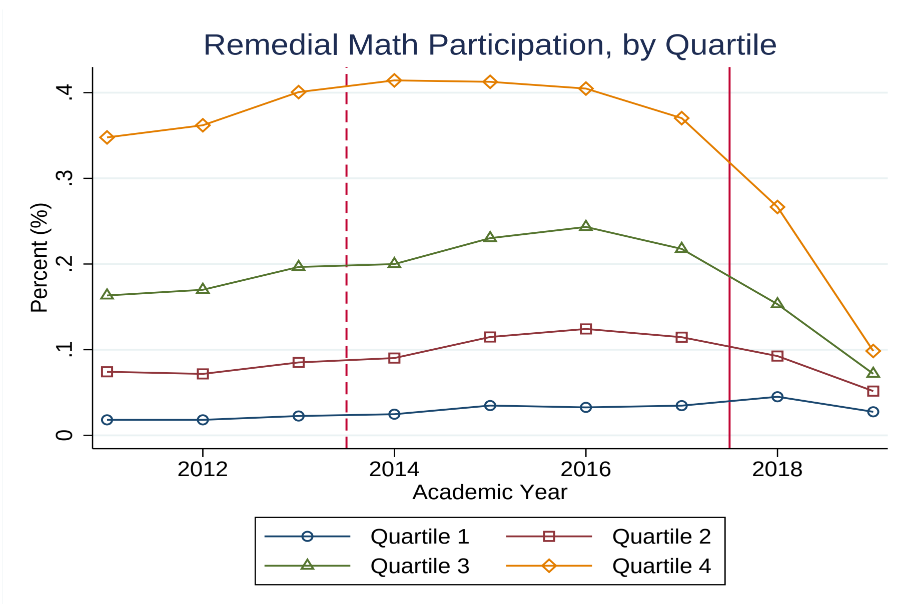
(b) Predicted Math Transfer-Level Course Taking

Notes: These two graphs show the predicted proportion of students taking transfer-level English or math courses throughout time. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

Figure 3: Observed Remedial Course Participation, by Quartile



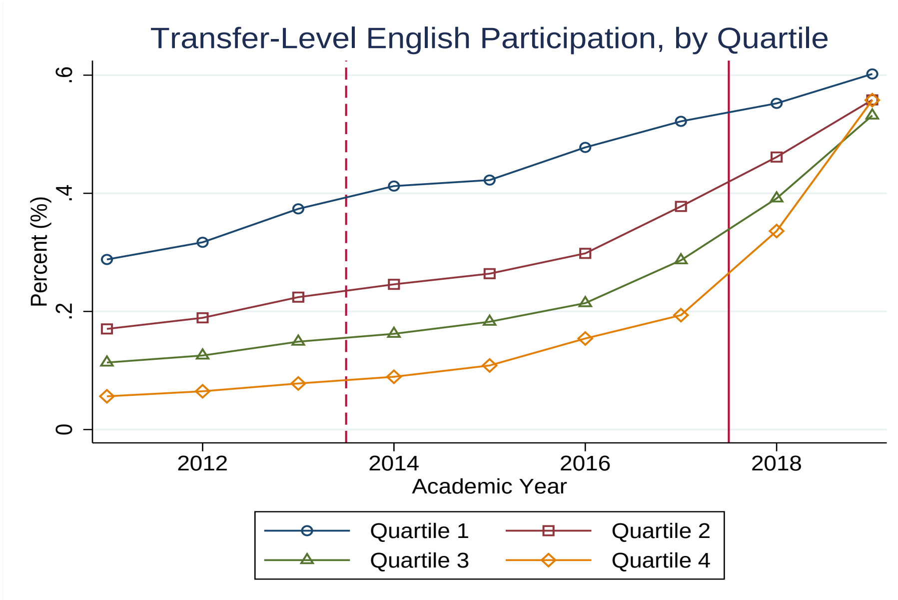
(a) Remedial English Course Taking, by Quartile



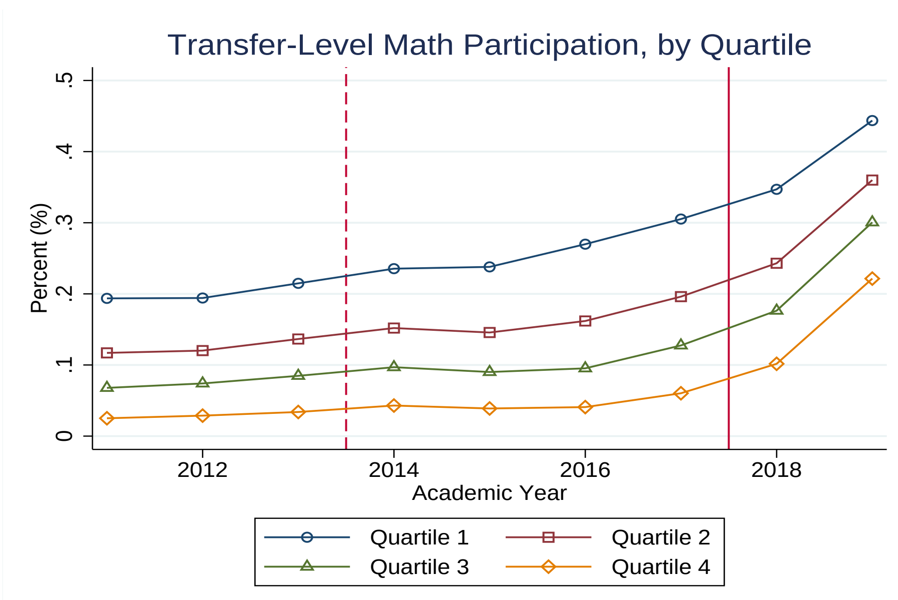
(b) Remedial Math Course Taking, by Quartile

Notes: These two graphs show the observed proportion of students taking remedial English or math courses throughout time. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

Figure 4: Observed Transfer-Level Course Participation, by Quartile



(a) Transfer English Course Taking, by Quartile



(b) Transfer Math Course Taking, by Quartile

Notes: These two graphs show the observed proportion of students taking transfer-level English or math courses throughout time. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

Table 2: English Course Taking and Outcomes, By Quartile

Remedial English	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt (5)
Intermediate	0.016**	0.009**	0.028***	0.028***	0.005
	(0.007)	(0.004)	(0.009)	(0.010)	(0.015)
After	-0.073***	0.012***	-0.004	-0.076***	-0.230***
	(0.012)	(0.004)	(0.009)	(0.012)	(0.021)
Average	0.173	0.016	0.076	0.194	0.420
Observations	951506	239698	238324	237718	234091
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X
Transfer-Level English	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt (5)
Intermediate	0.110***	0.139***	0.108***	0.093***	0.080***
	(0.007)	(0.014)	(0.010)	(0.009)	(0.009)
After	0.310***	0.237***	0.293***	0.319***	0.370***
	(0.014)	(0.021)	(0.018)	(0.017)	(0.022)
Average	0.180	0.333	0.201	0.134	0.069
Observations	951506	239698	238324	237718	234091
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X
Pass Rates	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt (5)
Intermediate	0.097***	0.129***	0.095***	0.081***	0.068***
	(0.006)	(0.011)	(0.008)	(0.007)	(0.007)
After	0.265***	0.229***	0.258***	0.269***	0.284***
	(0.010)	(0.015)	(0.011)	(0.012)	(0.014)
Conditional Pass Rates					
Before	0.772	0.793	0.774	0.758	0.806
Intermediate	0.882	0.928	0.880	0.871	0.850
After	0.855	0.966	0.881	0.843	0.768
Average	0.139	0.265	0.154	0.100	0.054
Observations	951506	239698	238324	237718	234091
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the "average" is calculated using only students enrolled in community college before any policy change (2011-2013). Each panel represents different binary outcomes, separately by quartile and overall: 1) whether or not the student took remedial English, 2) whether or not the student took transfer-level English, and 3) whether or not the student passed their transfer-level English course with a C or better. The conditional pass rate is calculated by dividing the coefficient on the proportion of students who passed with a C or better by the coefficient on the proportion of students taking a transfer-level English course. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Table 3: Math Course Taking and Outcomes, By Quartile

	Overall	1st Qrt	2nd Qrt	3rd Qrt	4th Qrt
Remedial Math	(1)	(2)	(3)	(4)	(5)
Intermediate	0.024***	0.012***	0.033***	0.039***	0.017*
	(0.005)	(0.003)	(0.007)	(0.009)	(0.010)
After	-0.056***	0.020**	-0.001	-0.062***	-0.178***
	(0.010)	(0.009)	(0.008)	(0.009)	(0.018)
Average	0.170	0.020	0.080	0.182	0.379
Observations	951506	228026	241467	242209	238062
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X
	Overall	1st Qrt	2nd Qrt	3rd Qrt	4th Qrt
Transfer-Level Math	(1)	(2)	(3)	(4)	(5)
Intermediate	0.045***	0.058***	0.042***	0.033***	0.024***
	(0.004)	(0.009)	(0.006)	(0.005)	(0.003)
After	0.161***	0.158***	0.160***	0.157***	0.134***
	(0.010)	(0.016)	(0.011)	(0.011)	(0.012)
Average	0.102	0.205	0.129	0.077	0.030
Observations	951506	228026	241467	242209	238062
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X
	Overall	1st Qrt	2nd Qrt	3rd Qrt	4th Qrt
Pass Rates	(1)	(2)	(3)	(4)	(5)
Intermediate	0.036***	0.049***	0.036***	0.024***	0.016***
	(0.003)	(0.007)	(0.005)	(0.003)	(0.002)
After	0.112***	0.126***	0.112***	0.100***	0.079***
	(0.007)	(0.012)	(0.009)	(0.007)	(0.007)
Conditional Pass Rates					
Before	0.696	0.741	0.672	0.636	0.667
Intermediate	0.800	0.845	0.857	0.727	0.667
After	0.696	0.797	0.700	0.637	0.590
Average	0.071	0.152	0.086	0.049	0.020
Observations	951506	228026	241467	242209	238062
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the “average” is calculated using only students enrolled in community college before any policy change (2011-2013). Each panel represents different binary outcomes, separately by quartile and overall: 1) whether or not the student took remedial math, 2) whether or not the student took transfer-level math, and 3) whether or not the student passed their transfer-level math course with a C or better. The conditional pass rate is calculated by dividing the coefficient on the proportion of students who passed with a C or better by the coefficient on the proportion of students taking a transfer-level math course. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Table 4: Transfer Units, By English Quartile

	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt. (5)
Transfer Units Attempted					
Intermediate	1.037***	0.826***	0.925***	1.022***	1.218***
	(0.054)	(0.095)	(0.071)	(0.066)	(0.063)
After	2.361***	1.841***	2.191***	2.448***	2.749***
	(0.081)	(0.133)	(0.096)	(0.094)	(0.113)
Average	9.09	9.52	8.36	7.67	7.12
Transfer Units Earned					
Intermediate	0.872***	0.719***	0.787***	0.823***	1.013***
	(0.039)	(0.066)	(0.055)	(0.051)	(0.061)
After	1.571***	1.403***	1.473***	1.514***	1.665***
	(0.062)	(0.101)	(0.080)	(0.067)	(0.091)
Average	6.92	7.71	6.35	5.67	5.09
Observations	951506	239698	238324	237718	234091
Completion Rate					
Before	0.761	0.810	0.760	0.739	0.715
Intermediate	0.841	0.870	0.851	0.805	0.832
After	0.665	0.762	0.672	0.618	0.606
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). Each panel represents different discretely continuous outcomes, separately by quartile and overall: 1) the number of transfer units attempted and 2) the number of transfer units earned. The completion rate is calculated by dividing the coefficient on the number of transfer units earned divided by coefficient on the number of transfer units attempted. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Table 5: Overall Units, By English Quartile

	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt. (5)
Total Units Attempted					
Intermediate	0.696***	0.641***	0.733***	0.684***	0.707***
	(0.069)	(0.096)	(0.086)	(0.073)	(0.097)
After	1.130***	1.069***	1.125***	1.157***	1.155***
	(0.091)	(0.115)	(0.104)	(0.098)	(0.145)
Average	11.04	10.93	10.52	10.24	10.16
Total Units Earned					
Intermediate	0.355***	0.470***	0.394***	0.253***	0.293***
	(0.044)	(0.072)	(0.060)	(0.052)	(0.059)
After	0.324***	0.680***	0.380***	0.173**	0.035
	(0.064)	(0.081)	(0.085)	(0.077)	(0.101)
Average	7.95	8.84	7.88	7.43	7.125
Observations	951506	239698	238324	237718	234091
Completion Rate					
Before	0.720	0.809	0.749	0.726	0.701
Intermediate	0.510	0.733	0.538	0.370	0.414
After	0.287	0.636	0.338	0.150	0.030
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). Each panel represents different discretely continuous outcomes, separately by quartile and overall: 1) the total number of units attempted, and 2) the total number of units earned. The completion rate is calculated by dividing the coefficient on total number of units earned by the coefficient on total number of units attempted. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Table 6: Course Taking, By Treatment Intensity

	Any (1)	Remedial (2)	Transfer-Level (3)	Pass C (4)
English				
Intermediate × Pr(Remed. Eng.)	-0.108**	-0.029	-0.112***	-0.111***
	(0.044)	(0.040)	(0.033)	(0.027)
1 S.D. Effect	[-1.7%]	[-0.4%]	[-1.8%]	[-1.7%]
After × Pr(Remed. Eng.)	-0.143**	-0.624***	0.291***	0.123***
	(0.058)	(0.052)	(0.070)	(0.045)
1 S.D. Effect	[-2.3%]	[-9.9%]	[4.7%]	[2.0%]
Average	0.472	0.173	0.180	0.139
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X
Math				
Intermediate × Pr(Remed. Math)	-0.146***	-0.027	-0.055***	-0.055***
	(0.035)	(0.034)	(0.017)	(0.014)
1 S.D. Effect	[-2.3%]	[-0.4%]	[-0.3%]	[-0.8%]
After × Pr(Remed. Math)	-0.323***	-0.549***	-0.057	-0.100***
	(0.047)	(0.072)	(0.049)	(0.030)
1 S.D. Effect	[-5.2%]	[-8.8%]	[-.9%]	[-1.6%]
Average	0.455	0.170	0.102	0.071
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). The coefficient of interest is the policy time period of interest interacted with the likelihood of enrolling in remedial courses. The outcome is a binary variable for whether or not the student took (a) any English/math course, (b) a remedial English/math course, (c) a transfer-level English or math course, and (d) passed the transfer-level course with a C or higher. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

Table 7: Overall Units, By Treatment Intensity

	Overall		Transfer-Level	
	Units Attempted	Units Earned	Units Attempted	Units Earned
	(1)	(2)	(3)	(4)
English				
Intermediate × Pr(Remed. Eng.)	0.081	-0.274	0.975***	0.853***
	(0.291)	(0.212)	(0.235)	(0.209)
1 S.D. Effect	[0.01]	[-0.44]	[0.16]	[0.14]
After × Pr(Remed. Eng.)	0.218	-1.394***	1.983***	0.573*
	(0.425)	(0.331)	(0.373)	(0.300)
1 S.D. Effect	[0.03]	[-0.22]	[0.32]	[0.09]
Average	10.37	7.62	8.09	6.08
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X
Math				
Intermediate × Pr(Remed. Math)	-0.279	-0.806***	1.230***	0.982***
	(0.237)	(0.208)	(0.276)	(0.262)
1 S.D. Effect	[-0.04]	[-0.13]	[0.20]	[0.16]
After × Pr(Remed. Math)	-0.300	-1.972***	2.277***	0.742**
	(0.366)	(0.324)	(0.469)	(0.371)
1 S.D. Effect	[0.05]	[-0.32]	[0.36]	[0.12]
Average	10.37	7.62	8.09	6.08
Observations	951506	951506	951506	951506
Student Controls	X	X	X	X
High School FE	X	X	X	X
College FE	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). The coefficient of interest is the policy time period of interest interacted with the likelihood of enrolling in remedial courses. The outcome is a binary variable for whether or not the student took (a) any English/math course, (b) a remedial English/math course, (c) a transfer-level English or math course, and (d) passed the transfer-level course with a C or higher. Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

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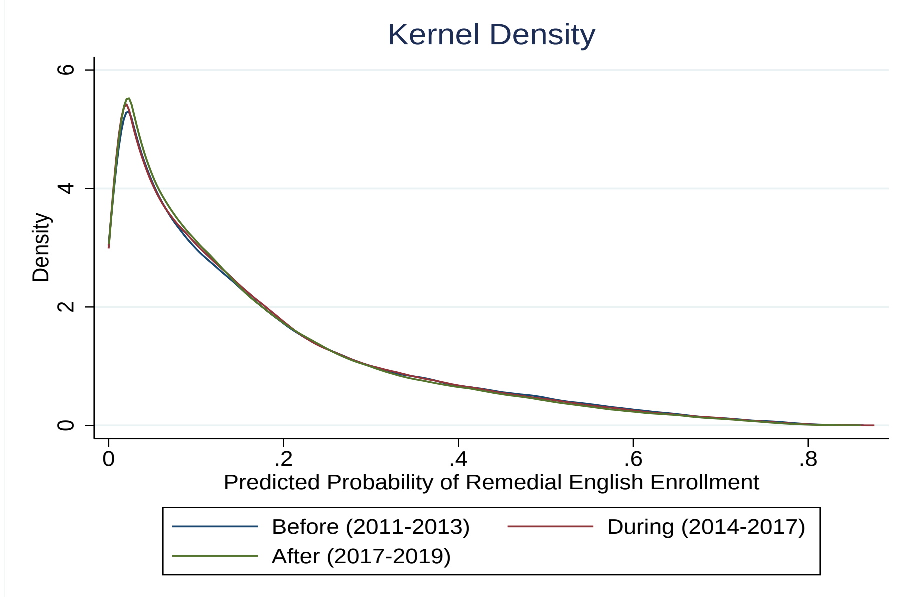
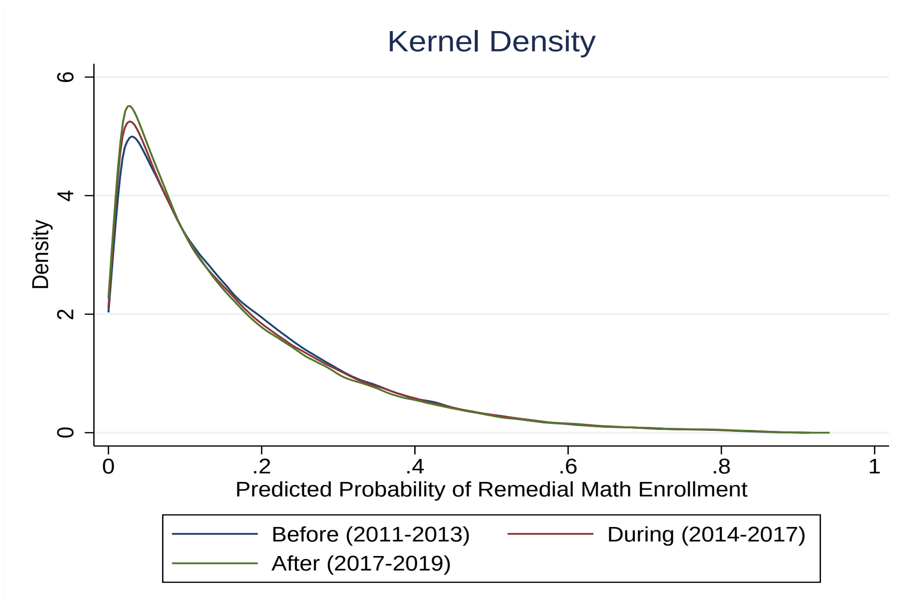
Appendix

Figure A1: Observed Course Participation

(a) Distribution of Predicted Probability of Remedial English Enrollment



(b) Distribution of Predicted Probability of Remedial Math Enrollment



Notes: These two graphs show distribution of the predicted probabilities of a student taking remedial English or math, by remedial policy time periods.

Table A1: Prediction Model Coefficients

	Remedial Eng. Status	Remedial Math Status
	(1)	(2)
ELA Z-Score × ELA Perf. Level	-0.176***	-0.088***
	(0.017)	(0.010)
ELA Z-Score^2	-0.297***	-0.105***
	(0.021)	(0.013)
Math Perf. Level	-0.110***	-0.434***
	(0.011)	(0.022)
ELA Z-Score	-0.165**	-0.081**
	(0.065)	(0.037)
Hispanic	0.171***	0.099***
	(0.032)	(0.036)
White	-0.176***	-0.100**
	(0.032)	(0.042)
Male	-0.189***	-0.267***
	(0.018)	(0.020)
Math Z-Score × Math Perf. Level	-0.018**	-0.086***
	(0.009)	(0.015)
Math Z-Score	0.037	0.108***
	(0.030)	(0.041)
Asian	0.180***	-0.345***
	(0.043)	(0.050)
Disabled	0.204***	0.149***
	(0.042)	(0.040)
Parent Education Level	0.026***	0.021***
	(0.005)	(0.005)
Age (in months)	0.010***	0.008***
	(0.001)	(0.001)
Economic Disadvantage	0.137***	0.077***
	(0.017)	(0.020)
Limited English Proficiency	0.114***	0.063**
	(0.041)	(0.026)
ELA Perf. Level	-0.294***	
	(0.016)	
Black		-0.062
		(0.051)
Math Z-Score^2		0.004
		(0.007)
Other Race		-0.057
		(0.045)
Constant	-0.487**	-1.655***
	(0.222)	(0.187)
Observations	281816	287989
Y Mean	0.176	0.165

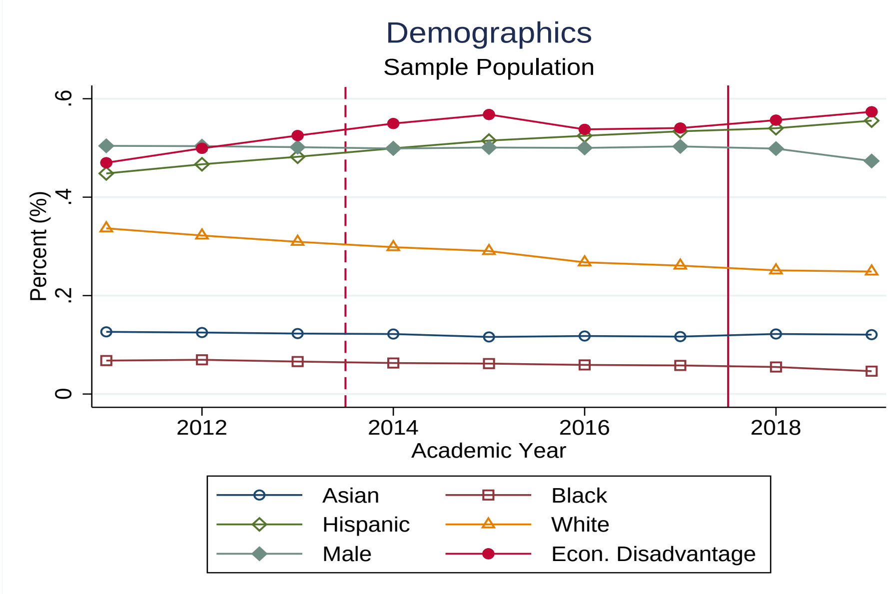
Notes: This table shows the predicted model coefficients used to predict each student's likelihood of enrolling in remedial English (or math, respectively) within the first semester of enrolling in community college.

Table A2: Student-Level Summary Statistics - Demographics

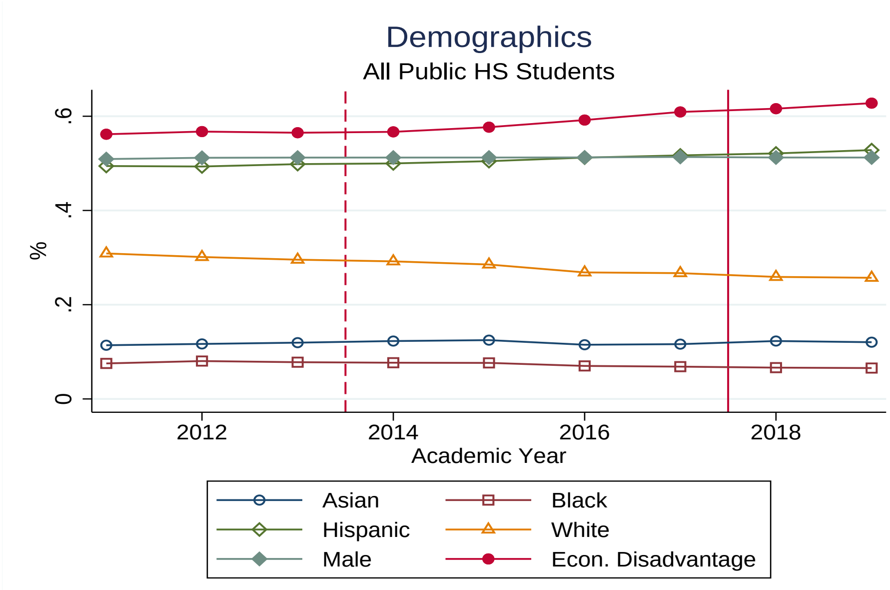
	All (F2011-SP2020)	Before (F2011-SP2013)	Intermediate (F2014-F2017)	After (SP2017-SP2020)
Male	0.498	0.501	0.499	0.491
	(0.500)	(0.500)	(0.500)	(0.500)
Disabled	0.0701	0.0602	0.0664	0.0914
	(0.255)	(0.238)	(0.249)	(0.288)
Asian	0.123	0.129	0.120	0.121
	(0.329)	(0.335)	(0.325)	(0.326)
Hispanic	0.509	0.464	0.521	0.549
	(0.500)	(0.499)	(0.500)	(0.498)
Black	0.0592	0.0652	0.0585	0.0522
	(0.236)	(0.247)	(0.235)	(0.222)
Other Race	0.0317	0.0290	0.0308	0.0374
	(0.175)	(0.168)	(0.173)	(0.190)
White	0.285	0.325	0.277	0.248
	(0.451)	(0.468)	(0.448)	(0.432)
Age (in months)	142.5	142.5	142.6	142.5
	(4.913)	(4.928)	(4.954)	(4.810)
Economic Disadvantage	0.535	0.492	0.550	0.566
	(0.499)	(0.500)	(0.497)	(0.496)
CST ELA Z-Score	-0.0221	0.00381	-0.0380	-0.0274
	(0.851)	(0.837)	(0.853)	(0.865)
CST Math Z-Score	-0.0590	-0.0368	-0.0622	-0.0806
	(0.904)	(0.976)	(0.888)	(0.839)
Pr(Remed. Eng.)	0.174	0.176	0.175	0.170
	(0.163)	(0.166)	(0.163)	(0.160)
Pr(Remed. Math)	0.163	0.165	0.164	0.160
	(0.150)	(0.148)	(0.151)	(0.150)
Observations	1213138	387780	549131	275857

Figure A2: Observed Course Participation

(a) Sample Population

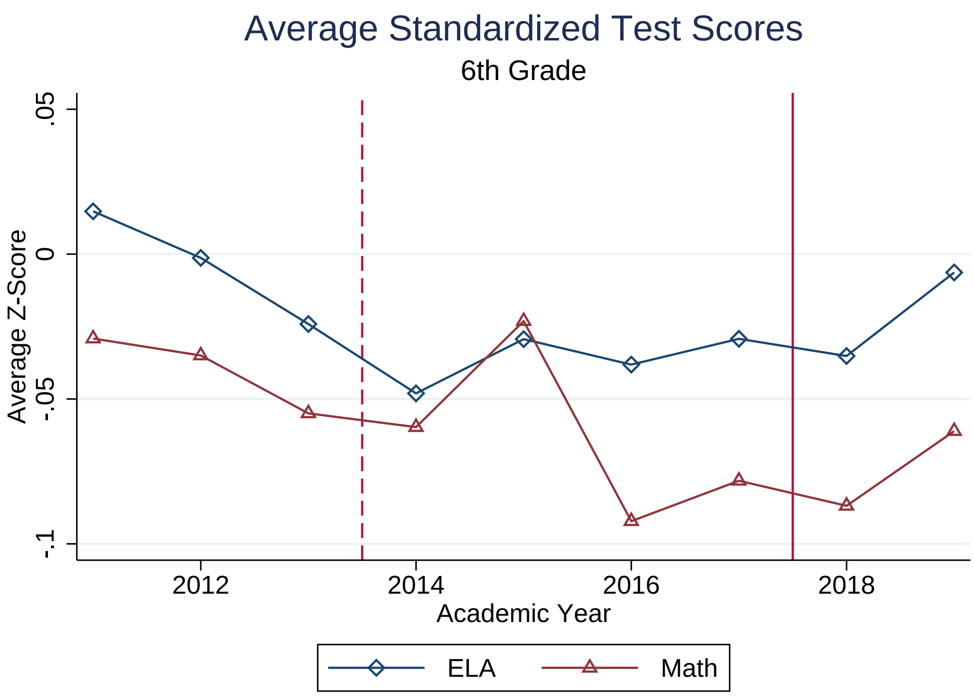


(b) All California Public High School Students



Notes: These two graphs show the demographic trends over time. Panel (a) represents the demographic trends over time for the sample population which consists of students who enroll in community college immediately after graduating high school. Panel (b) represents the demographic trends over time for all California public high school students. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

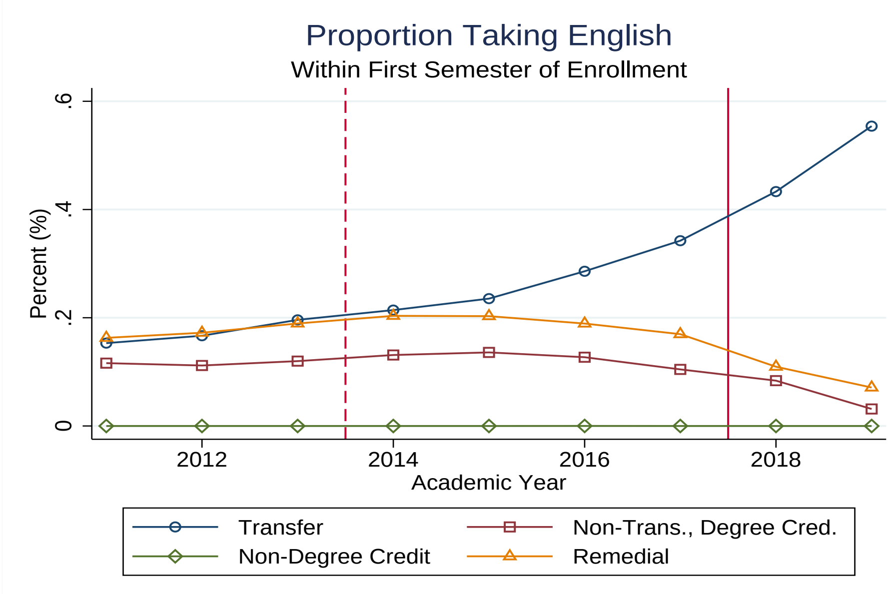
Figure A3: Average Standardized Test Scores over Time



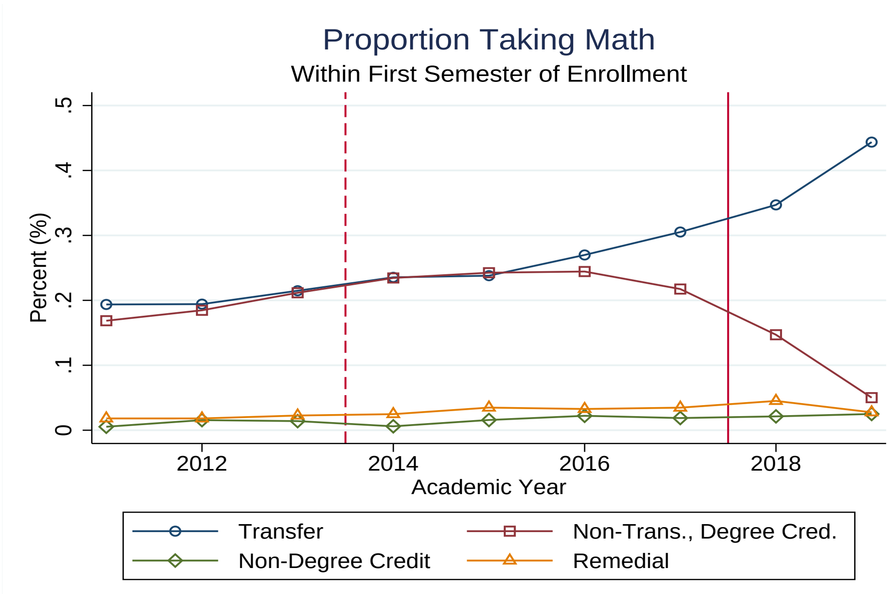
Notes: This graph shows the average standardized 6th grade test scores for students within each remediation policy period. To compare these exam scores across cohorts, I standardize each cohort's test scores by finding their z-score ($z = \frac{x-\bar{x}}{\sigma_x}$). The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

Figure A4: Observed Course Participation

(a) English Course Taking



(b) Math Course Taking

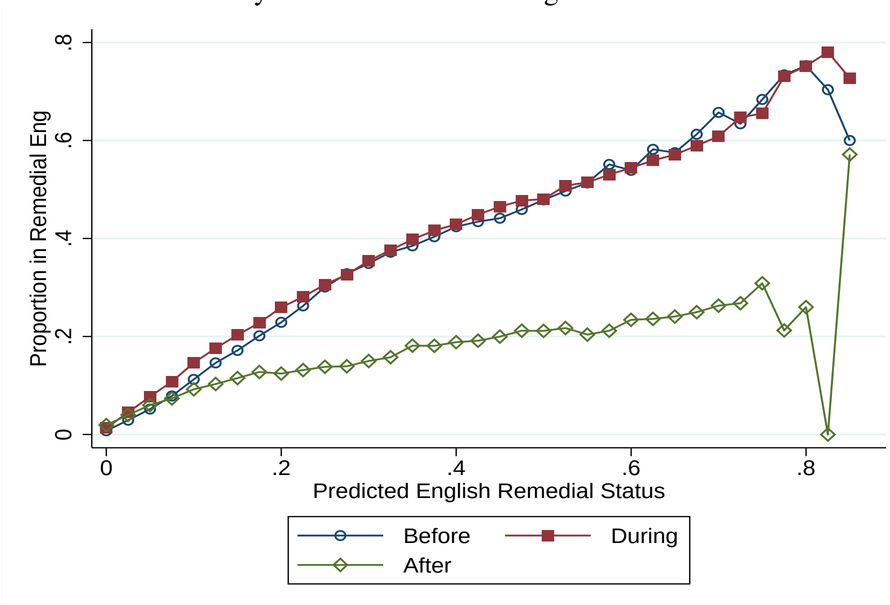


Notes: These two graphs show the actual proportion of students taking English (math) courses, by type over time. The red dashed line represents when remediation placement policies in 2013 were implemented, and the red solid line in 2017, when AB 705 was passed.

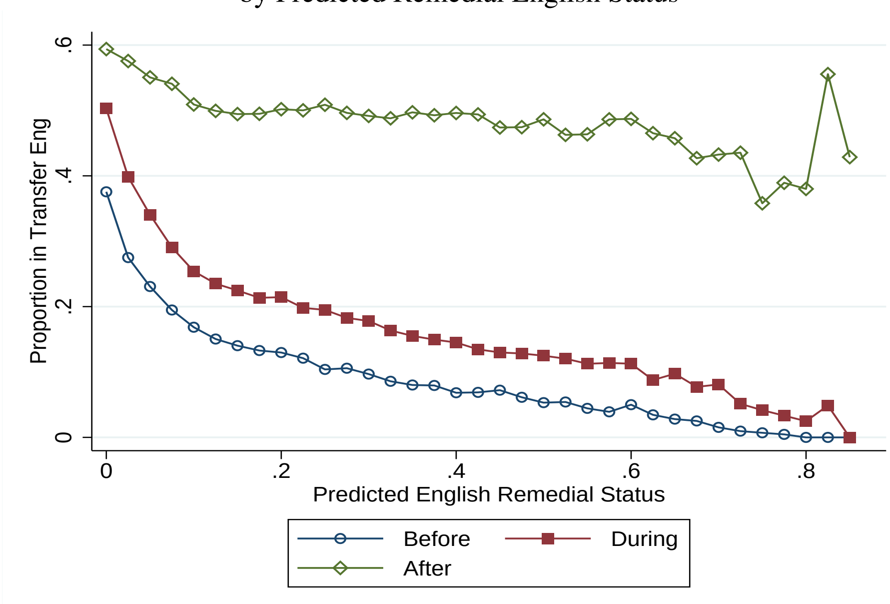
List of Covariates Included in Lasso Process:

- Age (in months)
- Age^2
- Age^3
- 6th Grade ELA Standardized Scale Score
- 6th Grade ELA Standardized Scale Score^2
- 6th Grade ELA Standardized Raw Score
- 6th Grade ELA Performance Level
- 6th Grade ELA Performance Level $\times$ 6th Grade ELA Standardized Scale Score
- 6th Grade Math Standardized Scale Score
- 6th Grade Math Standardized Scale Score^2
- 6th Grade Math Standardized Raw Score
- 6th Grade Math Performance Level
- 6th Grade Math Performance Level $\times$ 6th Grade Math Standardized Scale Score
- Parent's Education
- Socioeconomic Disadvantaged
- Asian
- Black
- Hispanic
- White
- "Other" Race
- Disability
- Limited English Proficiency
- Gender
- Language
- English Proficiency Level
- Migrant
- Reclassified English Proficiency
- Charter School
- Gifted and Talented
- 6th Grade Science Subject
- 6th Grade Science Raw Score
- 6th Grade History Subject
- 6th Grade History Raw Score
- CST Math Subject

(a) Proportion of Students Enrolled in Remedial English, by Predicted Remedial English Status



(b) Proportion of Students Enrolled in Transfer English, by Predicted Remedial English Status



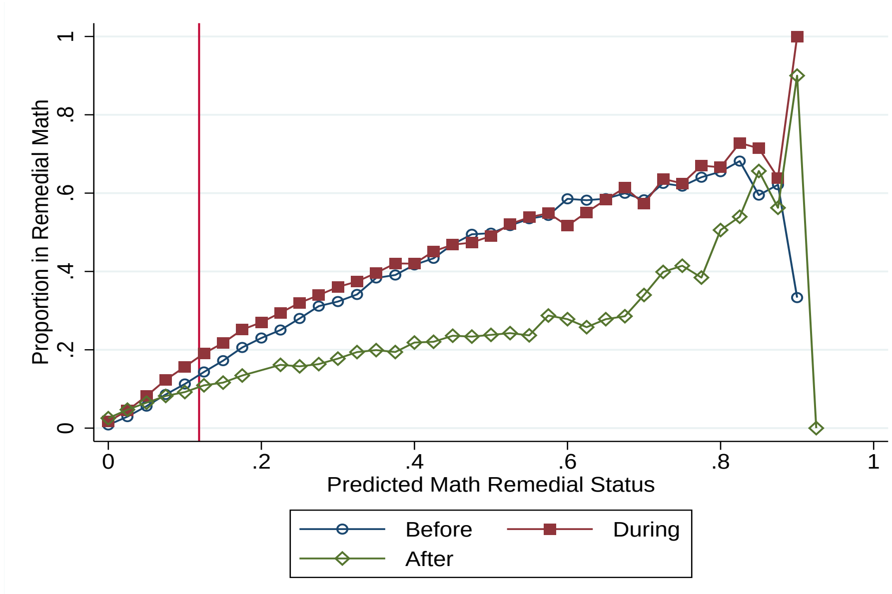
Notes: These two graphs show the proportion of students actually taking remedial English courses (panel a) or transfer-level English (panel b), by their predicted remedial English status. Each line represents a different remediation policy time period.

Table A3: Overall Units, By Math Quartile

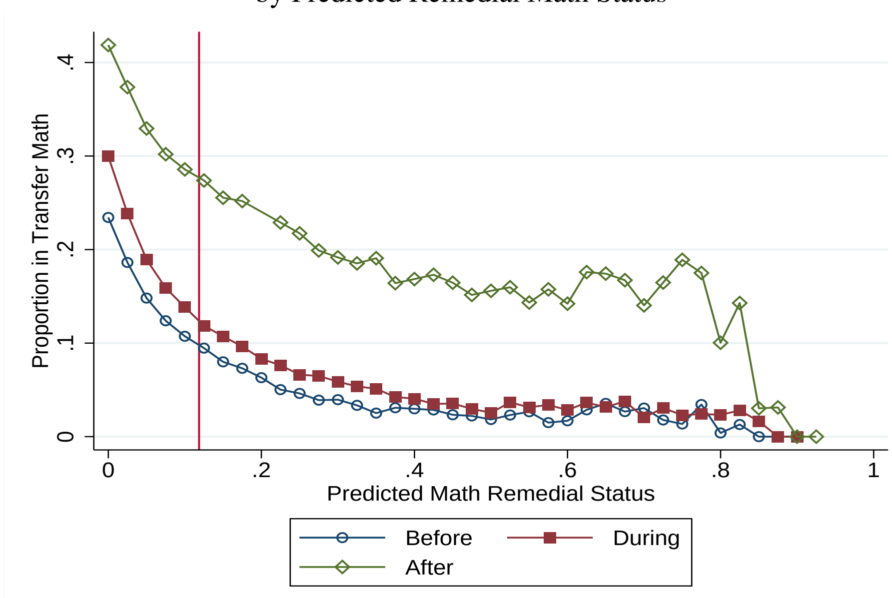
	Overall	1st Qrt	2nd Qrt	3rd Qrt	4th Qrt.
	(1)	(2)	(3)	(4)	(5)
Total Units Attempted					
Intermediate	0.696***	0.721***	0.715***	0.697***	0.626***
	(0.069)	(0.099)	(0.079)	(0.082)	(0.076)
After	1.130***	1.132***	1.123***	1.143***	1.085***
	(0.091)	(0.121)	(0.095)	(0.108)	(0.124)
Average	10.37	10.83	10.64	10.38	10.16
Total Units Earned					
Intermediate	0.355***	0.537***	0.424***	0.274***	0.187***
	(0.044)	(0.071)	(0.056)	(0.053)	(0.051)
After	0.324***	0.758***	0.391***	0.165**	-0.047
	(0.064)	(0.083)	(0.077)	(0.083)	(0.089)
Average	7.62	8.63	8.54	7.56	7.11
Observations	951506	228026	241467	242209	238062
Completion Rate					
Before	0.735	0.797	0.803	0.728	0.700
Intermediate	0.510	0.745	0.593	0.393	0.299
After	0.287	0.670	0.356	0.144	0.043
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.

(a) Proportion of Students Enrolled in Remedial Math, by Predicted Remedial Math Status



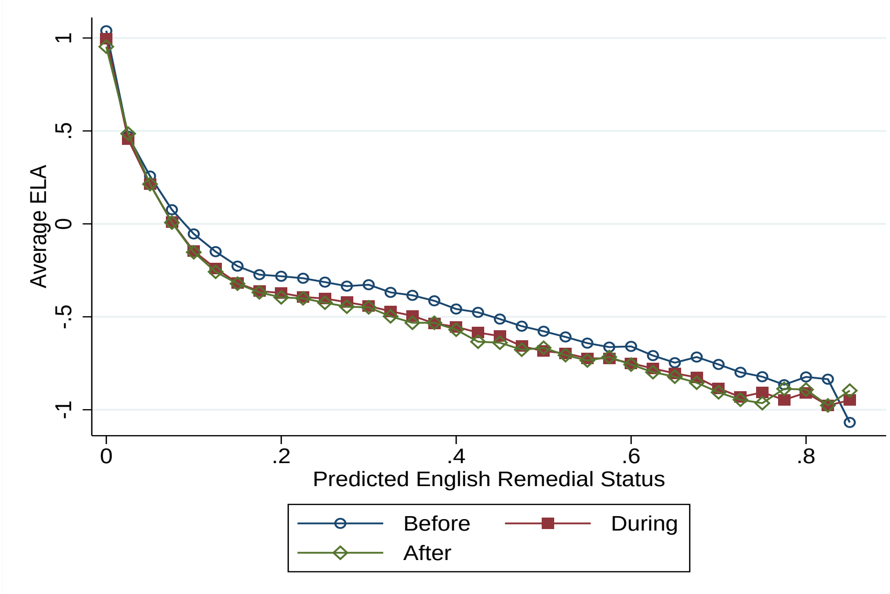
(b) Proportion of Students Enrolled in Transfer Math, by Predicted Remedial Math Status



Notes: These two graphs show the proportion of students actually taking remedial math courses (panel a) or transfer-level math (panel b), by their predicted remedial math status. Each line represents a different remediation policy time period.

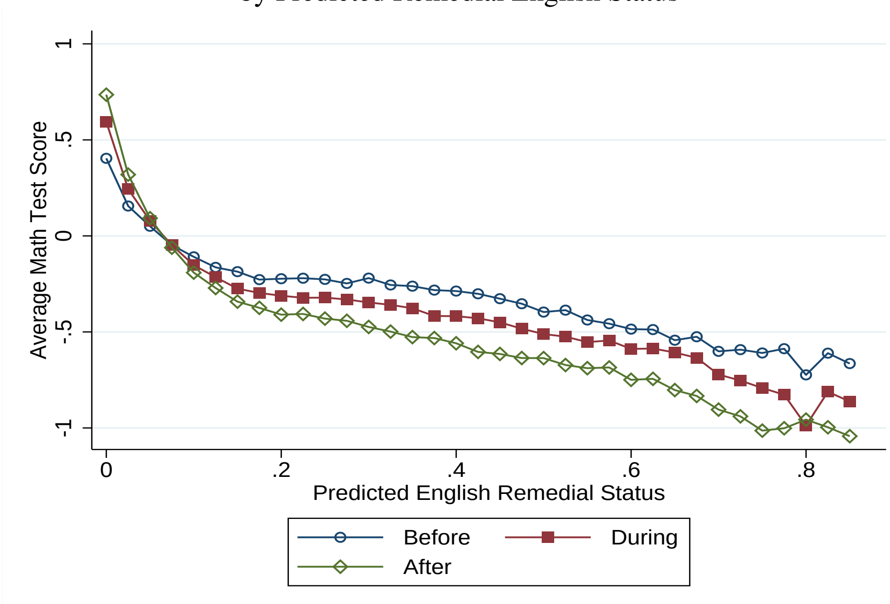
(a) Average ELA Z-Score of Students

by Predicted Remedial English Status



(b) Average Math Z-Score of Students,

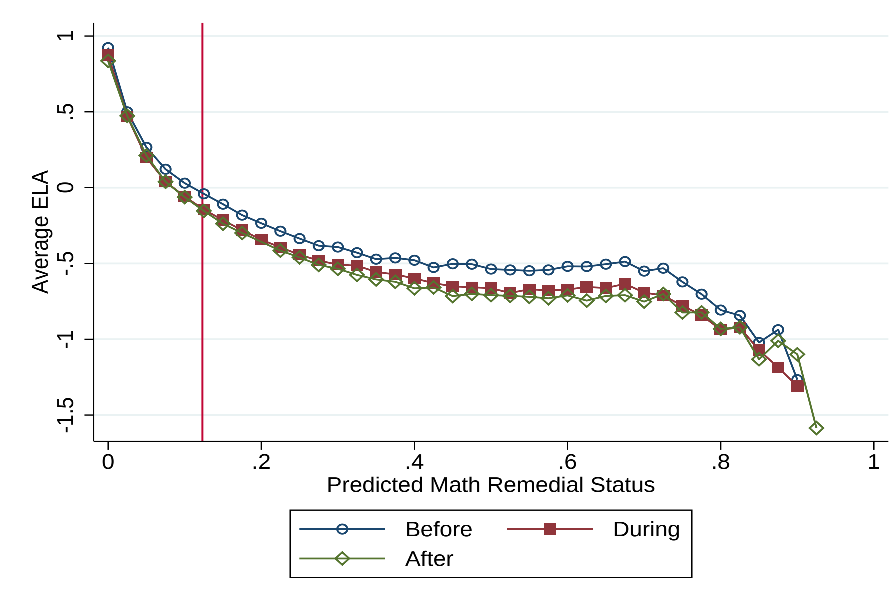
by Predicted Remedial English Status



Notes: These two graphs show the average standardized ELA or math test score, by students' predicted remedial English status. Each line represents a different remediation policy time period.

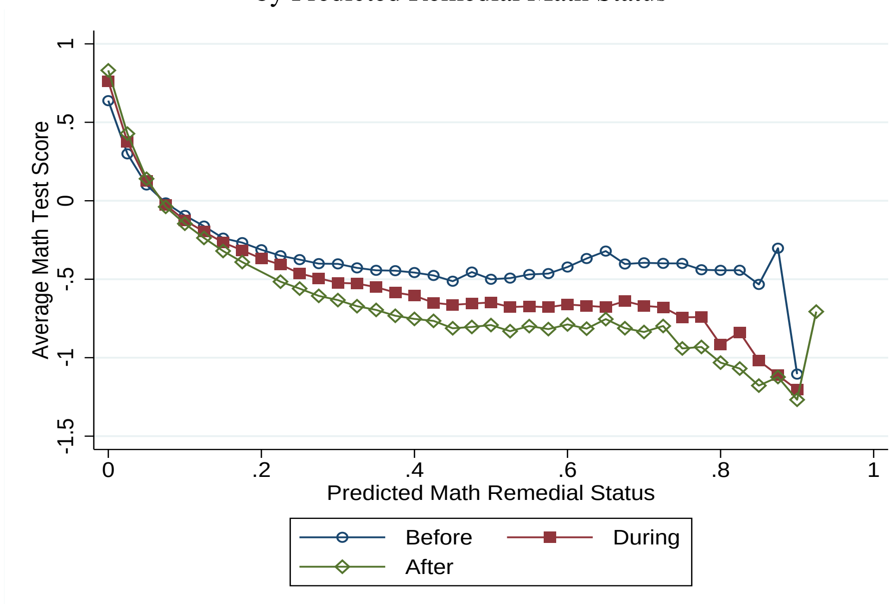
(a) Average ELA Z-Score of Students,

by Predicted Remedial Math Status



(b) Average Math Z-Score of Students,

by Predicted Remedial Math Status



Notes: These two graphs show the average standardized ELA or math test score, by students' predicted remedial math status. Each line represents a different remediation policy time period.

Table A4: Transfer Units, By Math Quartile

	Overall (1)	1st Qrt (2)	2nd Qrt (3)	3rd Qrt (4)	4th Qrt. (5)
Transfer Units Attempted					
Intermediate	1.037***	0.845***	0.896***	0.988***	1.235***
	(0.054)	(0.104)	(0.065)	(0.063)	(0.064)
After	2.361***	1.847***	2.151***	2.464***	2.724***
	(0.081)	(0.146)	(0.091)	(0.091)	(0.112)
Average	8.09	9.52	8.54	7.85	7.02
Transfer Units Earned					
Intermediate	0.872***	0.717***	0.773***	0.831***	1.007***
	(0.039)	(0.079)	(0.051)	(0.043)	(0.062)
After	1.571***	1.418***	1.452***	1.531***	1.631***
	(0.062)	(0.110)	(0.072)	(0.068)	(0.092)
Average	6.08	7.69	6.55	5.81	5.02
Observations	951506	228026	241467	242209	238062
Completion Rate					
Before	0.752	0.808	0.767	0.740	0.715
Intermediate	0.841	0.849	0.863	0.841	0.815
After	0.665	0.7628	0.675	0.621	0.599
Student Controls	X	X	X	X	X
High School FE	X	X	X	X	X
College FE	X	X	X	X	X
Predicted Treatment Intensity	X	X	X	X	X

Notes: For purposes of comparison, the average is calculated using only students enrolled in community college before any policy change (2011-2013). Student controls include indicators for gender, disability, race, and socioeconomic disadvantaged, with linear controls for age (in months), and standardized test scores. Standard errors are clustered at the community-college level.