The Expansion of Multiple-Measure Placement Policies During COVID-19: A Case Study of the Kentucky Community and Technical College System

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Abstract

Because of their open enrollment policies, community colleges serve large numbers of students whose K–12 education has left them unready to succeed in college-level courses. Colleges typically use test scores such as the ACT to place students into appropriate course levels. However, the use of test-based measures alone has been criticized as being an incomplete measure of students' ability. As a result, most colleges have begun to use high school grade point average (HSGPA) to supplement placement policy. We examine one such reform enacted across the 16 colleges in the Kentucky Community & Technical College System (KCTCS). We find that the number of students deemed college ready upon entrance to KCTCS substantially rose after HSGPA was added and that HSGPA is a stronger predictor of passing gateway courses than ACT scores. Newly college ready students based on HSGPA but not ACT scores generally had weaker first-year outcomes than students who met ACT college readiness benchmarks, but the gaps in gateway course enrollment and completion narrowed during the study period. However, we are unable to attribute the narrowing of these gaps solely to the use of HSGPA because of other concurrent developmental education reforms.

1. Introduction

Community colleges are broad-access institutions designed to provide a wide variety of higher education opportunities to a diverse population. To meet the needs of students with varying skill levels, students who seek postsecondary credentials are assessed and placed into appropriate levels of courses upon matriculation. Students who do not meet college readiness benchmarks for their academic plan are assigned to supplemental support, commonly known as developmental education (DE), to remedy the identified skill deficiencies.

During the COVID-19 pandemic, community colleges across the United States adopted more flexible DE assessment and placement policies (Bickerstaff et al., 2022). With the limitations on in-person testing, many colleges waived test-based evidence of college readiness and shifted toward using multiple measures, particularly high school grades, for placement decisions. The shift to multiple measures assessment (MMA)[1] was not new. It started more than a decade ago after research found that test score–based placement policies misassigned at least a quarter of students who could have succeeded in college-level courses to developmental courses (Belfield & Costa, 2012). But the pandemic accelerated the trend of moving away from test-based placement policies. As of spring 2021, 26 states allowed the use of MMA for developmental placement decisions (Whinnery & Odekar, 2021).The assessment and placement policy waiver adopted by the Kentucky Community & Technical College System (KCTCS) is one such example. In addition, according to a nationally representative survey of 2-year colleges, 73% of colleges were using non-test-based indicators of high school performance in their placement systems in 2023 (Litschwartz et al., 2023).

[1] Technically, colleges have always allowed the use of multiple types of assessment to demonstrate college and career readiness (e.g., ACT, SAT, and Accuplacer scores can often be used interchangeably). In the DE placement literature, MMA specifically refers to the use of nontest measures like high school grades along with test scores for assessment and placement of incoming students (Bickerstaff et al., 2022).

To provide students with appropriate levels of support when most testing centers were inaccessible, KCTCS decided to allow its colleges to exempt students from existing assessment and placement criteria. In place of test-based measures, unweighted, overall high school grade point average (HSGPA) could be used to determine a student's academic readiness for college coursework. The policy waiver in spring 2020 was later extended through 2022 when HSGPA was officially incorporated into KCTCS' assessment and placement policy.

The outcomes of students who received higher course placement under the more flexible policy are uncertain. Proponents of MMA argue that HSGPA reflects both the academic and nonacademic skills of a student (Bailey & Jaggars, 2016), and empirical evidence suggests that it is a stronger predictor for college success than standardized test scores such as the ACT (e.g., Allensworth & Clark, 2020). However, our interviews with KCTCS faculty revealed widely shared concerns, particularly in math. They were worried that the overall HSGPA was a poor indicator of math proficiency, a concern that echoes the views of many faculty and staff members reported in other research studies (e.g., Kopko et al., 2023; Ngo et al., 2021). This concern also is likely exacerbated by the "no fail" or "no zero" grading policies adopted by an increasing number of K–12 schools in recent years.[2] In addition, under the pandemic-related waivers, students in the "bump-up" zone (i.e., students who do not meet test-based benchmarks but have sufficiently high HSGPA) receive higher course placement, but no students receive lower course placement. This is distinct from a more holistic MMA system in which multiple sources of evidence are combined, and student course placement could go up or down.

Driven by these considerations, this study examines the outcomes associated with the HSGPA-based waiver adopted by KCTCS. Kentucky is one of the few states that require all

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[2] For example, see https://www.nea.org/nea-today/all-news-articles/teachers-divided-over-controversial-no-zero-grading-policy?form=MG0AV3.

11th-grade students in its public schools to take the ACT. The availability of both ACT test scores and HSGPA allows us to answer these research questions:

(1) For students who were bumped up in course placement under the waiver between 2020–21 and 2022–23, how did their college outcomes compare to those for students who met ACT-based college readiness criteria?

(2) How did the outcomes of students in the bump-up zone compare to the outcomes for similar students in prior years when they would have been required to undertake more DE?

(3) Is there evidence that bumped-up students could have benefitted from more DE support based on data for similar students from the prewaiver period?

We focus on four early metrics that are shown to strongly predict later college success (Jenkins & Bailey, 2017): gateway math and English course enrollment and completion within the first year, persistence to the second year, and attempting 15 or more credits during the first year.

In addition to the three main research questions, we directly address faculty concerns about HSGPA by comparing its predictive power with the predictive power of standardized test scores. Further, we explore whether placement accuracy will improve if we use subject-specific HSGPAs; a weighted HSGPA that accounts for the rigor of high school courses; or a measure that aggregates test scores, HSGPA, and student and school characteristics with weights commensurate with how well each predicts first-year college outcomes. Because these measures most likely already exist in administrative records, any improvements in predictive accuracy can be achieved with minimal added costs.

We find that, among first-time freshmen who started a degree program in KCTCS between 2020–21 and 2022–23, those who were designated as college ready based on HSGPA alone tend to have weaker outcomes than students who met the ACT college readiness benchmarks. The gaps are the widest among historically underrepresented minority (URM) students. These differences are consistent with what one would expect based on their lower ACT scores. However, we also find that the gaps in gateway course enrollment and completion have been narrowing during the study period. Because of other ongoing DE reforms (e.g., an increasing number of gateway course options and changes in how support was delivered), these improvements can only be attributed to the combined effect of these reforms instead of the use of HSGPA alone. Finally, students in the bump-up zone in the prewaiver period generally did not benefit from the type of supplemental support they received, except that math DE in that period led to a higher likelihood of advancing to the second year and a marginally higher likelihood of attempting at least 15 credits in the first year.

Using predictive analytics, we find that HSGPA is a stronger predictor than ACT scores in math and English for passing a gateway course in the first year among community college students. Subject-specific and weighted HSGPAs improve prediction accuracy only marginally. The choice of prediction method (linear, logistic, and gradient-boosted methods) also does not make much of a difference. Overall, our analysis suggests that the current college readiness criteria under the KCTCS HSGPA-based waiver is very similar in practice to a holistic MMA that combines ACT scores and HSGPA with benchmarks set to predict a 60% success rate in gateway courses.

In the rest of this paper, we first review the related literature in Section 2 before providing more details about KCTCS assessment and placement policies and waivers in Section

3. Study design, including sample and data, sample characteristics, and empirical strategies, is presented in Section 4. Section 5 reports study findings, and Section 6 concludes with some discussion about lessons learned and the potential implications for MMA policies postpandemic.

2. Background and Related Literature

Whether HSGPAs or standardized test scores are the better predictors of college outcomes has been subject to decades of debate (e.g., Allensworth & Clark, 2020; Buckley et al., 2018; Friedman et al., 2025). A key concern with HSGPA is its comparability across schools, teachers, and classes. For example, the variation in college completion rates across high schools increases by 26% in statistical models that control for HSGPA, which suggests that the same grades from different high schools reflect different levels of proficiency, and that it is harder for students to get high grades in higher performing schools than similar students in lower performing schools (Allensworth & Clark, 2020). On the other hand, a major concern with standardized test scores is their close correlation with racial/ethnic and socioeconomic background. For example, family income, race, and parental education are found to explain about four and a half times as much of the variance in ACT/SAT scores as with high school grades (Geiser, 2017). Regardless of which measure we use to predict college outcomes, the predictive power appears to vary substantially across high schools, and a large portion of the cross-school variation in college outcomes cannot be captured by either measure (Allensworth & Clark, 2020; Rothstein, 2004).

Accurate DE placement is challenging, and it has both efficiency and equity implications. Single-source, test-only placement policies were found to misplace 25% or more of students who could have succeeded in introductory college courses (Belfield & Costa, 2012; Scott-Clayton et al., 2014). Underplacement delays student exposure to college-level instruction, adding unnecessary costs in time and resources for students and institutions. DE participation also is unevenly distributed across student demographics. According to the National Center for Education Statistics, 78% of Black students and 75% of Hispanic students in community colleges are enrolled in DE, compared to 64% of White students (Chen, 2016). Furthermore, Black and Hispanic students take more DE courses (3.5 and 4 courses, respectively) than White students (2.4 courses). DE misplacement and overrepresentation of URM students in DE are particularly problematic when DE is ineffective, as is the case with traditional prerequisite remediation that often requires developmental students to take a long sequence of non-credit-bearing courses before reaching college-level courses, which in turn lowers their likelihood of earning their degree (Valentine et al., 2017).

Based on how course placement may change compared to test-only policies, MMA-based policies fall into two categories. Under the first category, students have a chance to be placed into higher level courses and no student will be placed lower. This category includes systems that use waivers (students are exempt from test-based criteria if they demonstrate college readiness through other measures like HSGPA) and sequential decision rules (students are screened using a predetermined sequence of measures where students failing test benchmarks are assessed using various nontest measures; Ganga & Mazzariello, 2019). Under the second category of MMA, students can be bumped up or down in course placement. This type of MMA uses placement formulas or algorithms that combine multiple measures of college readiness into a single score, often with weights that correspond to how well each measure predicts success in introductory college math and English courses using historical data.

Empirical evidence on the effect of moving away from the single-source, test-only placement practice is limited and somewhat mixed. The impact of the first type of MMA was evaluated in a randomized controlled trial (RCT) conducted in five community colleges in

Minnesota and Wisconsin (Cullinan & Biedzio, 2021). About 17,000 students were randomly assigned within each college to be assessed and placed using an experimental MMA policy that placed students using a sequence of decision rules in a predetermined order. For instance, an ACT score could be used first, and students who scored below the ACT benchmarks would be screened using the ACCUPLACER. Students failing to meet ACCUPLACER benchmarks would then be assessed using HSGPA. Students assigned to the control group were placed using the ACCUPLACER only.

With this design, no students were placed in lower level courses, and about 14–15% of students were placed higher. After three terms, students who received higher course placement were 11 percentage points more likely to complete college-level courses in math and 16 percentage points more likely in English. These gains are caused by large increases in college-level course enrollment. Students who were bumped up and enrolled in college-level math and English, however, were more likely to fail or withdraw from those courses (by 8 and 14 percentage points, respectively) than similar students who enrolled in a college-level course after taking DE under the control condition. A quick calculation using statistics reported in the study suggests that, among bumped-up students who enrolled in college-level courses, the odds of passing those courses are 1.9 in math and 2.1 in English. These are substantially lower than the odds of success among similar students in the control group (2.8 in math and 4.3 in English). All in all, the college-level course completion rate among all students was 2 percentage points higher in English for the treatment group and not statistically significantly different in the math completion rate, total college credits earned, or persistence.

The impact of the second type of MMA was evaluated in another RCT conducted in seven community colleges in the State University of New York (Barnett et al., 2020). In the study, researchers aggregated measures such as HSGPAs and test scores into a single MMA using weights based on how well each measure predicted college-level course outcomes in the past. Faculty at each college then chose cut points for DE placement. About half of the nearly 13,000 incoming students were assigned to the experimental placement system, and the other half were assigned to the colleges' existing placement system that mostly relied on the ACCUPLACER.

Compared with course placement under the existing system, 16% of students were placed higher and 10% were placed lower in math under the experimental system. In English, 44% of students were placed higher and 7% were placed lower. By the third term, students who were bumped up were 9 percentage points more likely to complete college math and English. These gains were offset by a decrease of 8–9 percentage points among students who were bumped down in course placement. Similar to the results reported in the Minnesota and Wisconsin study, the success rate in college-level courses was lower among bumped-up students than similar students in the treatment group (59% *vs*. 70% in math and 66% vs. 68% in English). Among all students, the course completion rate did not change significantly for math and increased by 3 percentage points for English. The study did not find a statistically significant difference in college credits earned, persistence, or degree attainment within five terms of initial enrollment. The magnitude of these estimates diminished further when students were tracked to the ninth term in a follow-up study (Kopko et al., 2023).

In addition to studies on the impact of shifting to MMA, our study is also related to the research on grade inflation and the predictive power of GPA. Research on grading standards indicates that students exposed to tougher standards tend to perform better on subsequent assessments, are more likely to enroll in college, and have higher future earnings (e.g., Betts &

Grogger, 2003; Figlio & Lucas, 2004; Hvidman & Sievertsen, 2021; Nordin et al., 2019). Conversely, lenient grading standards, although mechanically boosting students' GPA, increase student absences and lower student achievement (Bowden et al., 2023). The impact of grading standards varies by the skill levels of both the student and his/her class. High-achieving students in a lower achieving class benefit most from higher grading standards (Figlio & Lucas, 2004), and gains in GPA under lower grading standards are driven entirely by high-achieving students (Bowden et al., 2023). At the same time, grading leniency–induced absences are driven entirely by low-achieving students (Bowden et al., 2023). Heterogeneity in the impact of grading standards suggests that grade inflation may not necessarily render grades less informative.

3. KCTCS Assessment and Placement Policy and Waiver

KCTCS students who plan to earn postsecondary credentials (including associate degrees, diplomas, and certificates) are required to complete the KCTCS general education core curriculum at a level that corresponds to the credential. The core curriculum encompasses six competencies (e.g., written and oral communications and quantitative reasoning) designed to "enable students to develop their own values, pursue goals, and contribute to the political, moral, social, and cultural enrichment of society" (KCTCS, 2017, p. 72). The number of required general education credits varies by credential type. Associate degrees require 15 (Associate in Applied Science [AAS]) to 33 (Associate in Arts [AA] and Associate in Science [AS]) credits, a diploma requires six, and a certificate requires three.

Gateway courses—the lowest level courses that can fulfill general education requirements—also vary by credential type. For diplomas and certificates, the gateway courses (e.g., OST 108—Editing Skills for Office Professionals and OST 213—Business Calculations for the Office Professional) do not require students to demonstrate college readiness. By contrast, gateway courses for all associate degrees require students to meet college readiness benchmarks before enrollment, and those who do not meet the benchmarks are required to receive DE support. Therefore, associate degree–seeking students are the population of interest in this study.

College readiness benchmarks are identified by the Council on Postsecondary Education for a variety of assessments in math, English, and reading. Because academic readiness in reading can be met by fulfilling other graduation requirements, it does not impose an extra burden on students in practice.[3] As a result, our study focuses only on math and English. Most widely used assessments include the ACT, ACCUPLACER, ALEKS, EdReady, KYOTE, and the SAT. Because all Kentucky high school juniors take the ACT, ACT scores have been the primary measure of academic readiness. Students with a score of at least 19 in math and 18 in English are designated as college ready in those subjects in administrative records. In practice, however, students can choose among three math pathways that meet the need of their fields of study, and each pathway has a corresponding cutoff (22 for the College Algebra pathway, 19 for the Quantitative Reasoning pathway, and 16 for the Meta-major pathway; see Table A1 in the appendix).

In response to the COVID-19 pandemic, all 16 colleges within KCTCS asked to waive the assessment and placement requirements. Under the waiver, students with an unweighted HSGPA of 2.8 were generally considered academically ready in math and English.[4] Students with both a recognized test score and an HSGPA were placed at the highest levels demonstrated by either measure. Most students who started college in the postwaiver period (2020–21 through 2022–23) would have taken the ACT as high school juniors in the falls of 2018 through 2020.

[3] Specifically, students with 12 or more credit hours at the 100 level or above in any general education courses with a 2.0 GPA are considered college ready in reading. Because an associate degree requires at least 15 general education credits, students on track to completion will automatically meet the reading proficiency requirement.

[4] Consistent with this criterion, student-level records show a sharp jump in the likelihood that a student is designated as college ready at or above 2.8. An alternative cutoff at 2.5 was also discussed in some internal communications we reviewed from spring 2020. However, student records do not show any detectable change in the rate of readiness designation around 2.5.

The ACT remained mandatory even amid the pandemic, albeit with several accommodations designed to ensure student safety (e.g., spreading out test dates and implementing safety protocols at testing centers). As a result, HSGPA mostly served as a substitute for other test-based assessments that were no longer accessible in proctored settings during the pandemic. Access to those assessments gradually resumed as KCTCS test centers reopened in stages starting in 2022.

Figure 1 depicts the percentage of degree-seeking students deemed academically ready for college by subject, year, and measure. The percentage of students considered ready for college math had been declining before the placement policy waiver, dropping from more than 60% in the 2016–17 school year to less than 40% in the 2019–20 school year (Figure 1, Panel A). The math readiness percentage rebounded to 70% when HSGPA-based waivers took effect in 2020, but it started to fall again in subsequent years. English readiness follows a similar pattern (Figure 1, Panel B). It dropped from 80% to less than 60% during the prewaiver period, rebounded to about 75% immediately after the waiver, and then started to decline again to less than 60% in the 2022–23 school year.

In most years, about a quarter of the incoming freshmen were considered ready for college math and about a third for college English based on the ACT. The percentage of students designated as college ready in math through alternative assessments declined substantially in the prewaiver period from 38% in 2016–17 to 11% in 2019–20, which explains the overall decrease in college readiness during the period. In the postwaiver period, HSGPA enabled 38% of students to meet college readiness criteria for math in 2020–21, a percentage comparable to the contribution of alternative assessments in 2016–17. In English, HSGPA also replaced alternative assessments to help many students meet college readiness criteria. HSGPA remained an important measure to help students meet the academic readiness requirement in both subjects in 2022 and 2023.

4. Study Design

4.1 Sample and Data

Our study includes all first-time freshmen enrolled in a KCTCS degree program (including those who were undecided about their fields of study) who had valid ACT scores between 2017–18 and 2022–23. This study population excludes older and nontraditional students who do not have ACT scores or high school transcript data. However, because the ACT has been mandatory for high school juniors since 2006, the study population accounts for about 90% of all KCTCS students seeking associate degrees.

We use extant administrative data merged across the secondary and postsecondary levels. The secondary data cover ACT scores, student demographic characteristics, and transcript data, including HSGPA. The postsecondary data contain field and program of study, each course taken, grades and credits earned, and credential attainment at the 2-year and 4-year levels. Gateway courses and corequisites are identified by uniform course codes that are consistent across institutions.

4.2 Sample Characteristics

Our study includes more than 11,000 freshmen per year between 2017 and 2023. The average ACT scores dropped among incoming KCTCS students, averaging 18.3 in math and 18.9 in English in 2017, compared to 17.1 in math and 16.8 in English in 2023. The decline in ACT performance among KCTCS students is equivalent to 0.33 standard deviations in math and 0.41 in English, and it mirrors the national trend. During the same period, the national average ACT score dropped from 20.7 to 19.0 in math and from 20.3 to 18.6 in English (ACT, 2023).

However, we do not find a similar drop in HSGPA, which averaged 2.9 in 2017 and 3.0 in 2023. The diverging trends in grades and achievement can be construed as a sign of grade inflation.

We display the distributions of ACT scores and HSGPA for first-time degree-seeking students in Figure 2. In math, the bulk of students did not reach the ACT score of 19. In addition, among students who scored below 19, many students had the needed HSGPA of 2.8 (lower right quadrant). On the other hand, more than half of students met the English ACT college readiness requirement of 18. However, there is still a meaningful mass of students below the ACT cutoff but above the HSGPA cutoff in the lower right quadrant. Another notable pattern is that very few students who had the requisite ACT scores had GPAs below 2.8.

Summary statistics for math and English college readiness are shown in Tables 1 and 2. The placement policy waiver reshuffled incoming KCTCS students into college ready and nonready groups. While before the waiver, there were about the same number of ready and nonready students in math (Table 1), after the implementation of the waiver, there were nearly twice as many ready students as nonready students. The ratio of ready and nonready students in English, however, remained about 2 in both the pre- and postwaiver periods. In addition, ACT scores dropped in math, English, and reading while the percentage of students who are racial/ethnic minorities increased for both college ready and nonready students. HSGPA increased among college ready students and decreased among nonready students. Some of these changes may have been driven by factors other than the use of HSGPA for college placement.

In terms of first-year outcomes, the enrollment and passing rates in gateway math and English courses dropped among college ready students, but they either increased or did not change among nonready students. For example, after the policy waiver, 32% of college ready students passed introductory math in the first year of college (compared to 37% before the waiver). By comparison, 11% of nonready students passed introductory math after the waiver, which is statistically indistinguishable from the 12% before the waiver. The diverging time trends between college ready and nonready groups suggest that the more lenient placement policy may be associated with the lower overall passing rate among students considered college ready. The likelihood of attempting at least 15 credits in the first year dropped for both student groups, suggesting that these changes likely reflect the impact of the COVID-19 pandemic on student engagement. On the other hand, although persistence to the second year did not change or slightly improved for the college ready group, it dropped from 48% to 42% among students not ready in math and from 45% to 42% among students not ready in English.

4.3 Empirical Strategies for Student Outcomes Analysis

We investigate how the use of HSGPA in placement policies has shaped early college outcomes with the three research questions described in Section 1. Students in the bump-up zone—those who did not meet the ACT college readiness benchmarks but met the HSGPA requirements—are considered the treatment group. Students who met the ACT college readiness benchmarks (and were therefore unaffected by the waivers) are the comparison group.

4.3.1. Bumped-Up Students vs. Students Meeting ACT College Readiness Benchmarks

First, we compare the outcomes of students in the treatment and comparison groups while controlling for observable student characteristics ($\mathbf{X_i}$). Because we cannot control for student traits unobservable to researchers, this investigation should be viewed as exploratory, not causal. We estimate the following ordinary least squares (OLS) regression

$$Y_i = \beta_0 + \beta_1 TREAT_i + \mathbf{X_i}\boldsymbol{c} + \varepsilon_i, \text{(1)}$$

among a sample of students in the treatment and comparison groups. The coefficient β_1 represents the average difference in early college outcomes between these two groups of students, and it directly addresses KCTCS's question about how students whose course placement was bumped up based only on HSGPA fared relative to students who had the requisite ACT scores. We estimate Eq. (1) with and without controls. The interpretation of the results changes based on whether controls are included. In the version without controls, this represents the raw outcome gap between students who qualify based on ACT scores versus those who qualify based on HSGPA alone. This may be the most relevant information from a policy standpoint. We then add controls to estimate the extent to which the gap in outcomes between ACT-ready and HSGPA-ready students can be explained by differences in test-based measures of precollege skills. That is, given that the two groups are constructed such that one has higher ACT scores, we might expect this group to perform better because of prior preparation alone. Finally, we estimate the same OLS regression for URM and non-URM students to explore potential variation across student groups.

4.3.2. Outcome Trends for Students in the Bump-Up Zone Relative to Other College Ready Peers

Second, we use an event study model to examine whether students in the treatment group are better off in the postwaiver period than in the prewaiver period, relative to the pre-post change in outcomes among students in the comparison group. Comparison students are not affected by the waiver, and they are used to account for changes over time that may have affected all students. We use OLS to estimate the following model:

$$Y_{it} = \beta_0 + \beta_1 TREAT_i + TREAT * \boldsymbol{\delta_t \beta_{2t}} + \boldsymbol{\delta_t} + \mathbf{X_i}\boldsymbol{c} + \varepsilon_{it}, \quad (2)$$

where $\boldsymbol{\delta_t}$ is a series of year fixed effects with the year immediately before the waiver, 2019–20, left out as the reference period. $TREAT_i$ equals one if student *i* is in the bump-up zone, and $\mathbf{X_i}$ are student characteristics. $\boldsymbol{\beta_{2t}}$ is a vector of coefficients that reflects how the treatment–comparison gap in student outcome *Y* in Year *t* differs from the treatment–comparison gap in

2019–20. Estimated $\boldsymbol{\beta_{2t}}$ for years before the waiver took effect provides evidence on whether the treatment and comparison groups were following parallel trends during the baseline period. Under the assumptions that the average outcomes among the treatment and comparison groups would have followed parallel trends in the absence of treatment and that there are no contemporaneous policy changes that may also affect the outcomes, $\boldsymbol{\beta_{2t}}$ estimated for years after 2019–20 can be interpreted as the causal impact of switching to MMA-based placement policy.

Several concurrent changes pose an important threat to these identifying assumptions. The pandemic is a prime example; indeed, it is what prompted the waiver in the first place. The pandemic changed many aspects of life that could affect student progress through college. However, this would not impair the validity of the study design unless the pandemic had a *differential impact* on treatment and comparison students. If, for example, high school grades provide a better signal of students' ability to thrive during remote instruction than ACT scores, we could risk mistakenly attributing improved outcomes among students in the bump-up zone to the shift to MMA when the results reflect underlying differences in student ability across the groups. Although this is theoretically plausible, Figure 2 shows that it is rare for students who meet the ACT college readiness benchmarks (especially in math) to have an HSGPA below 2.8, and so the threat from differential impact of the pandemic may be limited.

A more concerning violation of the identification assumptions is the ongoing DE reforms carried out by KCTCS. The gateway courses that students can take to fulfill the "quantitative reasoning" core curriculum requirements expanded during the baseline period (Appendix Table A1). For example, PHI 250 (Symbolic Logic) was added in 2017–18 for students in AA and associate in fine arts (AFA) programs, MAT 151 (Introduction to Applied Statistics) was added in 2018–19 for students in AS programs, and MAT 141 (Liberal Arts Mathematics) was added in

2019–20 for students in all associate degree programs. The meaning of enrolling and completing gateway math has therefore changed over time. Course enrollment records show that new course options drew some students away from College Algebra, the traditional gateway math course in college (Table 3). However, College Algebra remained the most frequently taken gateway math course during the study period. There has been no similar gatekeeper course expansion for English, and English 101 was the primary course taken throughout the study period.

How DE support is delivered has also changed during the study period. Traditionally, students unprepared for college-level courses must enroll in prerequisite DE, which requires them to take a sequence of noncredit-bearing courses before enrolling in credit-bearing college courses. This model was gradually replaced by corequisite DE, which allows academically underprepared students to directly enroll in a credit-bearing, college-level course combined with paired developmental support. In 2016–17, corequisites accounted for 23% of all the DE courses students who scored below the ACT benchmarks took in math and 35% in English. In 2019–20, corequisite DE became available across all colleges in KCTCS, and the percentage of DE courses that are corequisite jumped to 49% in math and 85% in English (Table 4). The prevalence of corequisites remained stable in the years after 2020.

Because the 2019–20 school year is the reference point in our event study, gaps in student outcomes between the treatment and comparison groups during the postwaiver period are compared across years in which corequisite expansion had stabilized. This could mitigate the confounding influence of corequisite expansion on student outcomes. In addition, as a sensitivity check, we included a college-by-year measure of the prevalence of corequisite DE in Eq. (2) to account for any potential impact of corequisite DE on student outcomes. Our estimates are nearly identical with and without controlling for corequisite prevalence.[5]

4.3.3. Regression Discontinuity for Counterfactual DE Exposure

The third empirical strategy is using the prewaiver period as a laboratory to examine whether students in the bump-up zone could have benefited from DE. We restrict the sample to students from the 2017–18 through 2019–20 cohorts whose HSGPAs would have improved their course placement in 2020–21 and beyond. Some of these students met the ACT college readiness benchmarks, whereas others did not and received lower course placement. We estimate the effect of prewaiver course placement using a parametric regression discontinuity (RD) design in the following form:

$$Y_i = \alpha + \beta Treat_i + k(S_i) + \gamma Treat_i k(S_i) + \varepsilon_i, \quad (3)$$

where S_i is the difference between student *i*'s ACT score in math or English and their corresponding cutoffs and $k(S_i)$ is a polynomial function of the cutoff-centered ACT score. The discontinuity thus represents the benefit (if any) of DE exposure for students in the bump-up zone whose ACT scores are close to the DE cutoff. Although this procedure generates credibly causal estimates, a limitation of the approach is that most students who have an HSGPA of 2.8 or higher but do not meet ACT college benchmarks are actually quite far from the ACT cutoff (Figure 2). A key assumption of the RD design is that students scoring just above and below the ACT cutoffs are comparable, and conditional on the ACT score, these students are essentially randomly assigned to treatment and comparison conditions.

We use ACT scores from the 11th grade, when students took the test for the first time, and find no discontinuity in the distribution of scores around the cutoff. Because the optimal

[5] Results are available upon request.

bandwidth is about 3 points around the cutoff, we use a linear function of S_i. Finally, because ACT scores are not granular, we follow Kolesár and Rothe (2018) and use Eicker-Huber-White heteroskedasticity-robust standard errors for statistical inference. Results are similar when using other choices of bandwidth (Appendix Tables A3 and A4).

4.3.4. Empirical Strategies for Investigating Predictive Power

We address two sets of questions in this section. First, given the concerns that KCTCS faculty expressed about the predictive power of HSGPA, we examine how well HSGPA and ACT scores can predict passing college-level math and English courses using the receiver operating characteristic (ROC) curve. As with any prediction problems, predictions can be characterized as true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN; Appendix Table A2). These four types of prediction can then be aggregated in a variety of ways to reflect the strength of a predictor.

Instead of focusing solely on the overall rate of correct predictions, a ROC curve (e.g., Figure 4) highlights two aggregate measures of prediction accuracy. Specifically, it plots power (also known as "sensitivity" or TP rate, the proportion of students not ready for college-level courses who are correctly predicted to be not ready) against type-I errors (the proportion of college ready students who are wrongly predicted to be not ready). Distinguishing the types of correct (or incorrect) predictions is important because FPs and FNs have different policy implications. FPs can lead to wasted resources on students who do not need DE support, whereas FNs can result in students failing to receive the help they need to succeed. Depending on policy priorities and resource constraints, policy makers can place different weights on FPs and FNs when choosing DE cutoffs for a given predictor.

There is a tradeoff between power and type-I error. Power—the ability to correctly identify students who are truly not college ready—increases with the cutoff. But a higher cutoff (and hence higher power) also increases the type-I error. The 45-degree line in a ROC curve represents a predictor whose rate of correctly identifying problems equals the rate of erroneous predictions. That is, it represents a predictor as good as random. For stronger predictors, the rate of correct prediction should outpace that of erroneous predictions, and their ROC curves will be concave. The concavity of the ROC curve, measured by the area under the curve (AUC), represents the predictive strength. We use AUC to compare the predictive strength of HSGPA and ACT scores using all available years of data. We also examine how the predictive strength of these measures may have changed over time using AUC, a pertinent question amid concerns about grade inflation and falling ACT test scores in recent years.

The second set of questions explores whether prediction can be improved by using different measures (weighted HSGPA and subject-specific GPA), a combination of measures (HSGPA, ACT scores, and student and school characteristics), and alternative prediction modeling (linear regression, logistic regression, and XGBoost, a gradient-boosted machine learning technique). Being able to pass gateway courses in math and English remains the goal of the prediction.

5. Results

5.1 Bumped-Up Students vs. Students Meeting ACT College Readiness Benchmark

Table 5 displays the results for the comparison of students in the bump-up zone (who classified as college ready based on their HSGPA and not ACT scores) versus students whose ACT scores qualified them as college ready. Panel 1 displays the raw differences between these two groups in four outcomes: (a) the enrollment and (b) passing rates of college-level math, (c) the likelihood that they attempted 15 or more credits, and (d) persistence to the second year in college. For each outcome, results are presented separately for all students, historically URM students, and non-URM students. Students in the bump-up zone (i.e., students placed higher because of the waiver) have weaker first-year outcomes than students who were deemed college ready based on ACT math. Students in the bump-up zone were 3 percentage points less likely to enroll in introductory college math courses and 5 percentage points less likely to complete those courses. They were also less likely to attempt 15 or more credits during the first year in college (by 3 percentage points) and to advance to the second year (by 5 percentage points).

Panel 2 displays the same results when controlling for cubic polynomials of students' ACT score (in math and English) and HSGPA, race/ethnicity, and gender. Taken together, Panels 1 and 2 of Table 5 suggest that, although students in the bump-up zone were less successful in college math courses than students who were college ready based on their ACT scores (Panel 1), they performed lower in a way that is entirely explained by their lower precollege achievement measured by the ACT (Panel 2). The finding that students in the bump-up zone are less academically prepared for college-level courses is consistent with findings from the two RCTs we reviewed earlier and not surprising, given that the comparison group is composed of students with higher ACT scores. This pattern is especially pronounced for URM students in the bump-up zone, who were much less likely than URM students who met ACT college readiness benchmarks to enroll in (by 10 percentage points) and pass (by 10 percentage points) gateway math courses in a way that is explained by the prior preparation controls: Once these controls are added, large differences in enrolling and passing college math disappear.

For English (Table 6), students in the bump-up zone were also less likely to attempt 15 or more credits during the first year in college (by 8 percentage points) and to advance to the second year (by 9 percentage points) than students who met the ACT benchmark for college

English. However, students in the bump-up zone for English took advantage of higher course placement under the waiver and enrolled in college English at a higher rate (by 7 percentage points). The increase in enrollment rate is almost entirely driven by non-URM students.

Gains in the enrollment rate in college English did not translate into a higher passing rate of college English. This suggests that students who received higher course placement under the waiver were those who were less likely to be able to pass college English courses. Once accounting for their lower incoming ACT scores, however (Panel 2), these students in the bump-up zone had a 5-percentage-point higher passing rate. This is consistent with precollege incoming skills (as measured by ACT scores) that provide additional information about the ability to succeed in those courses.

5.2 Outcome Trends for Students in the Bump-Up Zone Relative to Other College Ready Peers

Results from the event study analysis are reported in Table 7. Compared to the year immediately before HSGPA-based MMA was implemented, students in the bump-up zone were closing the gaps in gateway math and English enrollment (by about 5–6 percentage points in math and 7–12 percentage points in English) with students who met ACT college readiness benchmarks. For English, the course completion gap also narrowed by 5–7 percentage points. There is no statistically significant difference in the likelihood of taking 15 or more credits in the first year and the likelihood of advancing to the second year in college.

As discussed above, other nearly concurrent DE reforms are a key threat to a causal interpretation of these results. Estimates reported in Table 7 show clear evidence that enrollment and completion of college-level courses started to improve before HSGPA-based MMA was introduced. The improvement in gateway math course enrollment and completion in the 2018–19 school year coincided with the addition of applied statistics to gateway math course options

(Appendix Table A1), a significant departure from the traditional policy of requiring college algebra for all students. Further improvement in gateway course enrollment in math and English and course completion in math in 2019–20 coincided with the significant expansion of corequisite courses (Table 4). As a result, event study estimates cannot isolate the impact attributable to the shift to MMA alone. Rather, the combined DE reforms at KCTCS appear to have helped improve gateway course enrollment and completion rates among students in the bump-up zone relative to students who met ACT college readiness benchmarks.

5.3 Regression Discontinuity for Counterfactual DE Exposure

Figure 3 plots college outcomes by ACT score, with vertical lines representing the ACT college readiness cutoffs. Recall that the sample for this analysis consists of students who would have received higher course placement based on HSGPA should they have enrolled in 2021 or later, but who actually enrolled prior to 2021. Among this sample, falling just below the ACT cutoff in math is associated with a large increase (of 7 percentage points) in the probability of taking prerequisite courses and a large decrease (of 13 percentage points) in corequisite courses (Table 8). In other words, for math, RD primarily estimates the impact of prerequisite DE relative to corequisite DE at the ACT cutoff of 19. The reason many students who scored 19 or higher on math enrolled in corequisite DE despite being designated as college ready is because many chose to take the College Algebra pathway (Table 3), which has a higher college ready benchmark of 22. This is why there are two apparent discontinuities (one at 19, which is our focus, and the other at 22) in prerequisite and corequisite math enrollment in Figure 3.

Students just below the math cutoff of 19 were 3 percentage points less likely to take gateway math in the first year (Table 8). However, there is no statistically significant difference in passing gateway math courses, and students exposed to more prerequisite math were more likely than students exposed to more corequisite math to attempt 15 or more credits in the first year (only marginally significant at the 0.10 level) and to advance to the second year. After the adoption of MMA, students who would have had more exposure to prerequisite math were bumped up to corequisite math. Our estimates suggest that students in the bump-up zone could have benefited slightly from more prerequisite math in terms of credit and enrollment momentum even though enrollment in gateway math courses would decrease.

Unlike math, there are no multiple English pathways. At the cutoff of 18 on ACT English, RD estimates the impact of corequisite English relative to no DE. Our analysis found no statistically significant difference in any of the four Year 1 outcomes, suggesting that students in the bump-up zone for English would not have benefited by exposure to the type of DE students received in prewaiver years.

5.4 Another Look at the Predictive Power of HSGPA

In this section, we directly address the question of whether HSGPA is a good predictor of passing gateway courses in math and English relative to ACT scores. Because both measures are typically available for most students, we also ask whether each may reflect unique information about a student such that, in combination, a more predictive developmental placement measure could be found.

ROC analysis shows that unweighted, overall HSGPA is statistically significantly more predictive of passing gateway courses in math and English than ACT scores (Figure 4). This is consistent with recent findings from community colleges in California (Bracco et al., 2021) and Connecticut (Plourd, 2021). The estimated AUC for passing gateway math is 0.69 for HSGPA compared to 0.63 for ACT math. The estimated AUC for passing gateway English is 0.62 for HSGPA and 0.58 for ACT English. On the other hand, neither of these measures is a very strong predictor on its own. For reference, in predicting college enrollment using data from the Educational Longitudinal Study of 2002, HSGPA has an estimated AUC of 0.77, which is higher than the AUC of the number of extracurricular activities (0.64) or whether a student was ever enrolled in an AP course (0.56; Bowers & Zhou, 2019). In addition, the shrinking AUC suggests that the predictive strength of ACT scores has been declining in recent years, a pattern not seen with HSGPA (Figure 5).

The finding that HSGPA is a stronger predictor of first-year college success than ACT scores may appear to contradict the generally weaker outcomes for students in the bump-up zone relative to students who met the ACT benchmarks. This can be explained by the fact that most students who passed the ACT cutoff also had HSGPAs of 2.8 or higher (Figure 2). This could suggest that multiple measures may be warranted in DE placement policies; that is, even though HSGPA is the stronger single predictor, a minimum ACT performance threshold may still be needed.

Table 9 shows how the overall predictive accuracy for whether a student will pass a gateway course varies by predictors and prediction methods. The key takeaway is that a simple model that uses only the overall HSGPA and the ACT score in the relevant subject—the two primary placement measures used by KCTCS—performs nearly as well as more complicated models with subject-specific HSGPA (e.g., math or English GPA) and ACT scores in all subjects.[6] Model performance does not appear to be sensitive to the choice of prediction model (i.e., linear or algorithmic), which may not be surprising given the small number of predictors.

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[6] In results available from authors, we find that we can get a modest boost in prediction accuracy when including high school characteristics such as percentage of economically disadvantaged, percentage belonging to different racial groups, etc. However, it is unclear whether these are capturing the effect of these characteristics in and of themselves or, more likely, that these are serving as proxies for local human capital and economic conditions.

Because the linear model is simple, performs well, and is easy to interpret, we then use this model to form predictions of passing gateway math and English courses. Results are shown in Figure 6. Each isoquant represents different predicted probabilities of passing a college-level course given the prediction model described above. The slope of each isoquant represents the tradeoffs between HSGPA and the ACT for a given probability of passing college-level courses. Because HSGAP and ACT scores are on very different scales, we need to scale the coefficients in the linear prediction model by the standard deviation of each measure to understand the relative importance of each measure.[7] After the conversion, HSGPA receives about 5.4 times as much weight as ACT scores do for math and 5.7 times as much weight as ACT scores do for English. This is consistent with the variable importance metrics generated by XGBoost (see Appendix Figure A1).

The points on each isoquant represent all the combinations of HSGPA and ACT score that predict the same predicted success rate. For example, a student with a score of 22 on ACT math and an HSGPA of 3.2 is predicted to have about a 70% chance of passing a gateway math course. Students with an ACT math score of 19, on the other hand, would need an HSGPA of about 3.3 to have the same predicted likelihood. We compare these estimated probabilities to the actual KCTCS policy, represented by dashed lines. In math, the areas above and to the right of the dashed lines largely overlap with the area to the top right of the isoquant predicting a 60% success rate. For English, the actual policy also closely reflects the 60% isoquant. This suggests that, for both math and English, the actual policy is very close to one that deems college-ready students with at least a 60% chance of passing college-level math and English courses.

[7] The standard deviation is 0.63 for HSGPA, 3.63 for ACT math, and 5.09 for ACT English.

6. Discussion

The use of MMA in many colleges began as an emergency response to the need to assess and place students timely during the COVID-19 pandemic. The circumstances under which existing placement policies were waived have caused concern among administrators and faculty members regarding student outcomes. Our study provides some of the earliest answers to their questions.

Students who received higher course placement based on HSGPA alone generally had worse first-year outcomes than students who met ACT benchmarks (most of whom also met the HSGPA criterion). The only exception is the gateway English course enrollment rate, which is higher for students in the bump-up zone. However, the gaps between these two groups of students in first-year gateway course enrollment and completion were narrowing. Even though it is not possible to completely disentangle the unique contribution of the placement policy waiver from the effect of other aspects of DE reforms at KCTCS, evidence suggests that these reforms in combination have led to better short-run outcomes for students in the bump-up zone.

The inability to isolate the impact of shifting to MMA may be a limitation of the study. However, DE reforms often go hand in hand, and these reforms cannot be understood in isolation. Even with RCTs, previous estimates of the impact of MMA are conditional on the efficacy of DE at the time of the experiments: prerequisite DE. Because prerequisite DE has been found to have large negative effects on students, it is not surprising that students who were bumped up in those experiments had better outcomes, and those who were bumped down had worse outcomes. As another example, studies on the shift from prerequisite to corequisite DE typically estimate the combined effect of the corequisite reform and the math pathway reform, which tend to go hand in hand.

The importance of context in assessing the impact of MMA is also the reason we should continue to monitor student outcomes in the coming years. The cohorts we studied all had the opportunity to take the ACT in Grade 11 and were not fully impacted by the pandemic. However, between 2020 and 2024, the percentage of high school graduates who were college ready dropped from 40% to 30% in math and from 60% to 50% in English (ACT, 2024). The deterioration of precollege skills is likely to continue because of the deep learning loss among third to eighth graders. These students will enter college in the coming years, but postpandemic recovery has been slow and uneven. Even after taking into account the modest recovery of student learning, student achievement declined by almost half a standard deviation between 2019 and 2024 (Dewey et al., 2025), a loss equivalent to about 2 years of learning in Grades 8 – 9 and even longer in upper grades (Lipsey et al., 2012). At a time when more students lack foundational knowledge in math and English, some administrators and faculty start to question whether relaxing placement criteria and accelerating student access to college-level courses may still be appropriate (Kim, 2024).

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Tables and Figures

Table 1. Summary Statistics for Math College Readiness, Student Characteristics, and First-Year Outcomes in College

Student characteristics and outcomes	Overall	Non-College-Ready Pre	Non-College-Ready Post	Non-College-Ready p diff	College Ready Pre	College Ready Post	College Ready P diff
Precollege skills							
HSGPA	2.97	2.69	2.35	0.00	3.11	3.31	0.00
ACT Math	18.13	15.91	15.38	0.00	19.93	18.66	0.00
ACT English	18.29	16.16	14.58	0.00	20.28	18.87	0.00
ACT Reading	19.63	17.69	16.24	0.00	21.35	20.30	0.00
Student demographics							
White	0.75	0.71	0.67	0.00	0.82	0.78	0.00
Black	0.11	0.15	0.17	0.00	0.07	0.07	0.01
Hispanic	0.08	0.09	0.10	0.00	0.06	0.09	0.00
Asian	0.02	0.01	0.01	0.29	0.02	0.02	0.00
Other race	0.04	0.04	0.05	0.00	0.04	0.04	0.39
Female	0.58	0.59	0.57	0.00	0.56	0.60	0.00
Male	0.42	0.41	0.43	0.00	0.44	0.40	0.00
Year 1 college outcomes							
Take Prerequisite Math	0.26	0.47	0.34	0.00	0.17	0.10	0.00
Take Corequisite Math	0.11	0.09	0.14	0.00	0.11	0.11	0.59
Take Gateway Math	0.37	0.18	0.21	0.00	0.55	0.46	0.00
Pass Gateway Math	0.25	0.12	0.11	0.02	0.37	0.32	0.00
Total Math Credits Earned	1.70	0.88	0.97	0.00	2.25	2.28	0.20
College Math GPA	1.98	1.96	1.49	0.00	2.01	2.06	0.01
Year 1 Credits Earned	11.32	8.23	6.88	0.00	14.32	13.64	0.00
Took >=15 credits 1st year	0.61	0.53	0.45	0.00	0.72	0.66	0.00
Advance to 2nd year	0.55	0.48	0.42	0.00	0.62	0.62	0.27
Observations	85,098	25,238	11,708	36,946	27,068	21,084	48,152

Notes: Study sample includes first-time, degree seeking students at KCTCS. College readiness designation was obtained from KCTCS administrative records. Post period represents 2020 and beyond when HSGPA was added as a placement measure.

Table 2. Summary statistics for English College Readiness, Student Characteristics, and First-Year Outcomes in College

Student characteristics and outcomes		Non College Ready			College Ready		
	Overall	Pre	Post	p diff	Pre	Post	p diff
Precollege skills							
HSGPA	2.97	2.63	2.33	0.00	3.03	3.27	0.00
ACT Math	18.13	16.11	15.48	0.00	19.04	18.46	0.00
ACT English	18.29	13.85	13.29	0.00	20.04	19.07	0.00
ACT Reading	19.63	16.21	15.36	0.00	20.98	20.37	0.00
Student demographics							
White	0.75	0.68	0.64	0.00	0.80	0.79	0.00
Black	0.11	0.16	0.18	0.00	0.08	0.07	0.00
Hispanic	0.08	0.09	0.12	0.00	0.07	0.08	0.00
Asian	0.02	0.02	0.02	0.29	0.01	0.02	0.00
Other race	0.04	0.04	0.05	0.00	0.04	0.04	0.03
Female	0.58	0.55	0.55	0.00	0.58	0.60	0.00
Male	0.42	0.45	0.45	0.00	0.42	0.40	0.00
Year 1 college outcomes							
Take Prerequisite English	0.12	0.28	0.20	0.27	0.08	0.04	0.00
Take Corequisite English	0.16	0.25	0.35	0.00	0.10	0.08	0.00
Take Gateway English	0.55	0.33	0.46	0.12	0.65	0.59	0.00
Pass College English	0.39	0.21	0.23	0.00	0.48	0.43	0.00
Total English Credits Earned	2.66	2.07	1.94	0.00	2.98	2.83	0.00
College English GPA	2.18	2.03	1.65	0.00	2.24	2.31	0.00
Year 1 Credits Earned	11.32	7.54	6.60	0.00	13.02	13.43	0.00
Took >= 15 credits 1st year	0.61	0.49	0.45	0.00	0.69	0.66	0.00
Advance to 2nd year	0.55	0.45	0.42	0.00	0.60	0.61	0.00
Observations	85,098	15,717	10,576	36,946	36,589	22,216	58,805

Notes: Study sample includes first-time, degree-seeking students at KCTCS. College readiness designation was obtained from KCTCS administrative records. Post period represents 2020 and beyond when HSGPA was added as a placement measure.

Table 3. Percentage Distribution of Gateway Math and English Courses Taken by First-Year Students at KCTCS

Course	2017	2018	2019	2020	2021	2022	2023
Math							
Mat 150: College Algebra	72%	65%	56%	48%	54%	53%	50%
Mat 126: Technic Algebra & Trigonometry	8	9	13	13	9	9	8
Mat 146: Contemporary College Math	5	8	12	9	9	11	9
Mat 116: Technical Mathematics	4	5	4	6	6	6	7
Mat 151: Introduction To Applied Statis	0	0	1	5	3	4	6
Mat 110: Applied Mathematics	4	5	4	4	4	5	6
Mat 141: Liberal Arts Mathematics	0	0	0	5	4	3	4
English							
Eng 101: Writing I	94%	93%	93%	93%	93%	94%	94%
Eng 102: Writing II	4	5	5	5	5	4	5

Notes: The table shows the most frequently taken gateway courses by first-time, first-year students in degree programs at KCTCS.

Table 4. Percentage Distribution of Developmental Education Courses by Mode (Corequisite vs. Prerequisite), by Year and ACT Score

ACT score range	2017		2018		2019		2020		2021		2022		2023	
	coreq	prereq	coreq	prereq	coreq	prereq	coreq	prereq	coreq	prereq	coreq	prereq	coreq	prereq
Math														
16–18	22.9	80.2	19.9	82.9	18.3	84.6	48.5	61.7	48.8	58.7	47.4	61.2	49.2	59.7
19–21	63.2	37.6	59.3	41.0	54.8	45.2	88.3	12.6	91.6	11.0	91.9	10.4	83.0	19.0
English														
15–17	34.5	73.3	70.0	37.6	71.6	35.0	85.4	22.5	79.5	27.2	84.0	22.1	82.2	25.3
18–20	40.5	61.9	73.8	28.5	74.0	27.7	86.2	16.7	74.1	27.1	77.3	26.9	75.2	29.9

Notes: Sample consists of students who took at least one developmental course in the first year. Cells represent the percentage of developmental course takers who took either a corequisite course or a prerequisite course. Total percentages for each year and ACT score range can exceed 100% because some students took both prerequisite and corequisite courses.

Table 5. Math Outcomes of Students in the Bump-Up Zone Relative to Students Who Met ACT College Readiness Benchmark in Math

	Take Gateway Math	Pass Gateway Math	15 or more credits	Advance to 2nd Year
Panel 1: Without controls				
Bumped up (All)	-0.03***	-0.05***	-0.03***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Bumped up (URM)	-0.10***	-0.10***	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.03)
Bumped up (non-URM)	-0.01	-0.04***	-0.03***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)
Panel 2: With controls				
Bumped up (All)	0.01	0.01	0.02	-0.00
	(0.02)	(0.02)	(0.01)	(0.02)
Bumped up (URM)	0.04	0.02	0.14***	0.05
	(0.05)	(0.04)	(0.05)	(0.06)
Bumped up (non-URM)	0.01	0.01	0.00	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)

Notes: Differences in first-year outcomes between students who had higher course placement under the waiver and students who were deemed college ready based on ACT scores, 2020–21 through 2022–23. Regression with controls include cubic polynomials of students' ACT score in math and English and high school GPA, race/ethnicity, and gender. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

Table 6. English Outcomes of Students in the Bump-Up Zone Relative to Students Who Met ACT College Readiness Benchmark in English

	Take Gateway English	**Pass Gateway English**	**15 or more credits**	**Advance to 2nd Year**
Panel 1: Without controls				
Bumped up (All)	0.07***	0.01	-0.08***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
Bumped up (URM)	0.01	-0.05**	-0.06***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.03)
Bumped up (non-URM)	0.08***	0.02***	-0.07***	-0.09***
	(0.01)	(0.01)	(0.01)	(0.01)
Panel 2: With controls				
Bumped up (All)	0.07***	0.06***	-0.02	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)
Bumped up (URM)	-0.03	-0.02	0.00	-0.04
	(0.05)	(0.05)	(0.05)	(0.06)
Bumped up (non-URM)	0.08***	0.07***	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)

Notes: Differences in first-year outcomes between students who had higher course placement under the waiver and students who were deemed college ready based on ACT scores, 2020-21 through 2022-23. Regression with controls include cubic polynomials of students' ACT score in math and English and high school GPA, race/ethnicity, and gender. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

Table 7. Changes in Outcomes of Students in the Bump-Up Zone Relative to Students Who Met ACT College Readiness Benchmarks, by Outcome and Subject

	Take Gateway Course	Pass Gateway Course	15 or more credits	Advance to 2nd Year
Math				
2017 (Pre)	-0.06***	-0.04***	0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)
2018 (Pre)	-0.06***	-0.05***	-0.01	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
2019 (Pre)	-0.02	-0.02	-0.00	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
2020 (Pre)	*Excluded year*			
2021 (Post)	0.05***	0.03**	0.01	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
2022 (Post)	0.06***	0.01	-0.03*	-0.02
	(0.02)	(0.01)	(0.01)	(0.01)
2023 (Post)	0.03	-0.01	0.02	
	(0.02)	(0.02)	(0.01)	
English				
2017 (Pre)	-0.02	-0.02	-0.02	-0.04***
	(0.02)	(0.02)	(0.02)	(0.02)
2018 (Pre)	0.01	-0.02	-0.02	-0.06***
	(0.02)	(0.01)	(0.01)	(0.02)
2019 (Pre)	0.05***	-0.01	-0.01	-0.03**
	(0.02)	(0.01)	(0.01)	(0.01)
2020 (Pre)	*Excluded year*			
2021 (Post)	0.12***	0.07***	-0.01	-0.03**
	(0.02)	(0.02)	(0.01)	(0.01)
2022 (Post)	0.10***	0.06***	-0.02	-0.01
	(0.02)	(0.02)	(0.01)	(0.02)
2023 (Post)	0.07***	0.05***	0.02	
	(0.02)	(0.02)	(0.01)	

Notes: Coefficient estimates from a regression of a given outcome (shown in column header) on a set of interactions between year fixed effects and an indicator for whether a student was in the bump-up zone; i.e., had ACT scores below college readiness benchmarks but whose HSGPA met benchmark. Coefficients represent the impact of being in bump-up zone relative to the final year before the policy change, 2020. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

Table 8. Regression Discontinuity Estimates of Impact of Being Just Below College Ready Among Students in Bump-Up Zone Prior to Policy Change

	Take Prereq Course	**Take Coreq Course**	**Take Gateway Course**	**Pass Gateway Course**	**15 or more credits**	**Advance to 2nd Year**
Math						
Below ACT	0.07***	-0.13***	-0.03	-0.01	0.03*	0.04**
(All)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Below ACT	0.06	-0.13***	-0.06	-0.01	-0.03	-0.03
(URM)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Below ACT	0.07***	-0.13***	-0.03	-0.01	0.03*	0.05***
(non-URM)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
English						
Below ACT	0.01	0.11***	0.02	0.00	0.03	-0.02
(All)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Below ACT	-0.06	0.11**	0.02	-0.04	-0.01	-0.04
(URM)	(0.04)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)
Below ACT	0.02	0.12***	0.02	0.01	0.03	-0.02
(non-URM)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)

Notes: Each cell displays coefficient estimate from a regression discontinuity design regressing outcome denoted in column header on ACT scores, an indicator for being below the ACT college readiness benchmark, and an interaction between ACT scores and being below benchmark. Coefficients represent the estimated change associated with falling just below college readiness benchmarks among a sample of students whose GPA would have classified them as college ready if the GPA placement policy had been in place when they enrolled. For Math, ACT math is the running variable with a cutoff of 19, and for English, ACT English with a cutoff of 18. Bandwidth is set at 3. The model is estimated parametrically because of the discrete nature of ACT scores. Heteroskedasticity robust standard errors are used to calculate confidence intervals. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

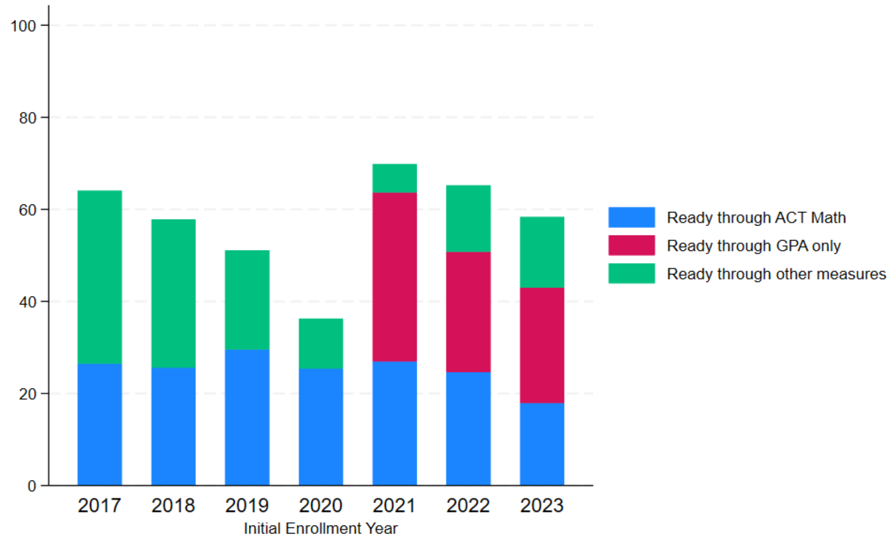
Table 9. Prediction Accuracy by Predictors and Estimation Method

	Predictors			
Estimation method and subject	ACT M/E/R HS GPA Subj HS GPA	Subj ACT HS GPA Subj HS GPA	Subj ACT HS GPA	Subj ACT Subj HS GPA
	XG Boost			
	(1)	**(2)**	**(3)**	**(4)**
Math	69.469%	69.229%	69.240%	68.020%
English	72.602%	72.596%	72.879%	72.254%
	Logistic			
	(5)	**(6)**	**(7)**	**(8)**
Math	67.666%	67.491%	67.656%	65.613%
English	71.067%	71.196%	71.512%	70.366%
	Linear			
	(9)	**(10)**	**(11)**	**(12)**
Math	68.994%	68.996%	69.116%	67.705%
English	72.430%	72.420%	72.670%	71.711%
Math N	36,599	36,599	40,474	37,439
English N	46,511	46,515	51,207	47,827

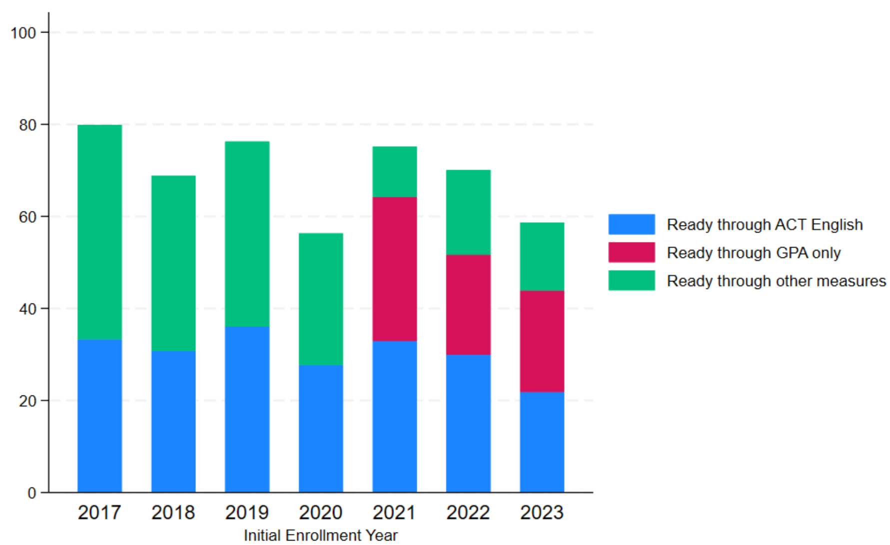
Notes: Displays the prediction accuracies of models predicting whether a student passes the first college-level math course or English course they enroll in, with separate models by subject. “Subj HS GPA” uses weighted high school GPA from the relevant subject and “Subj ACT” ACT scores from the relevant subject.

Figure 1. Percentage of First-Time Freshmen in KCTCS Who Are Considered Academically Ready for College, 2017–2023

(a) Math

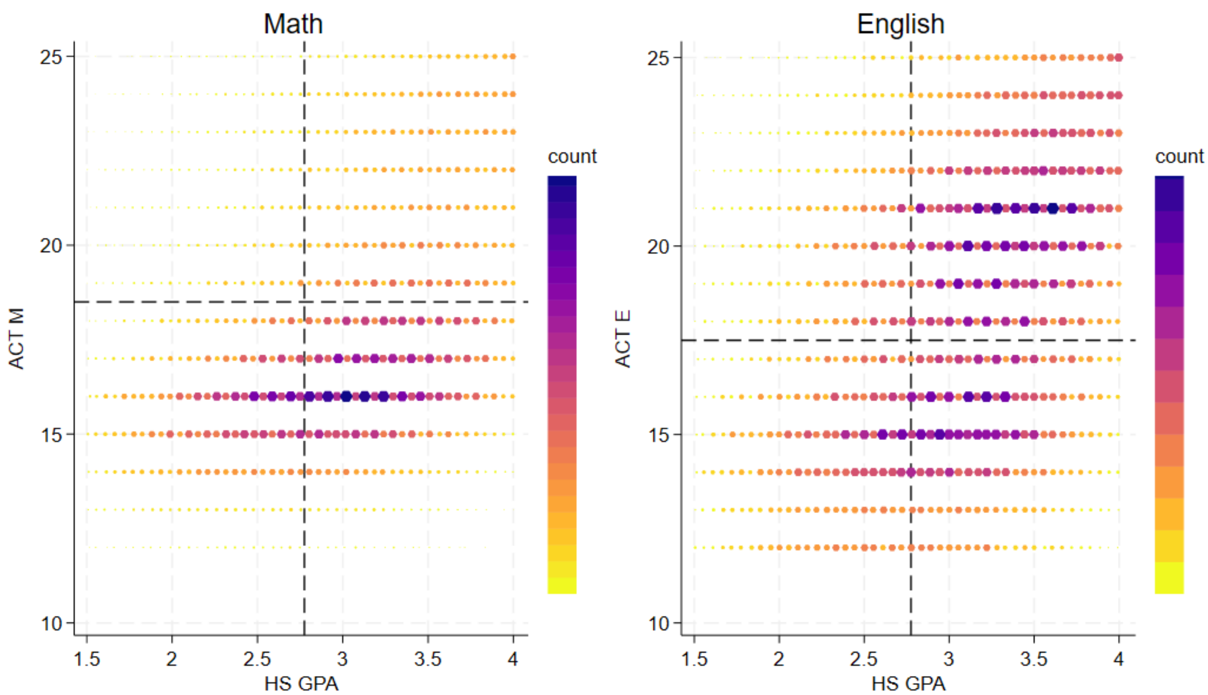


(b) English



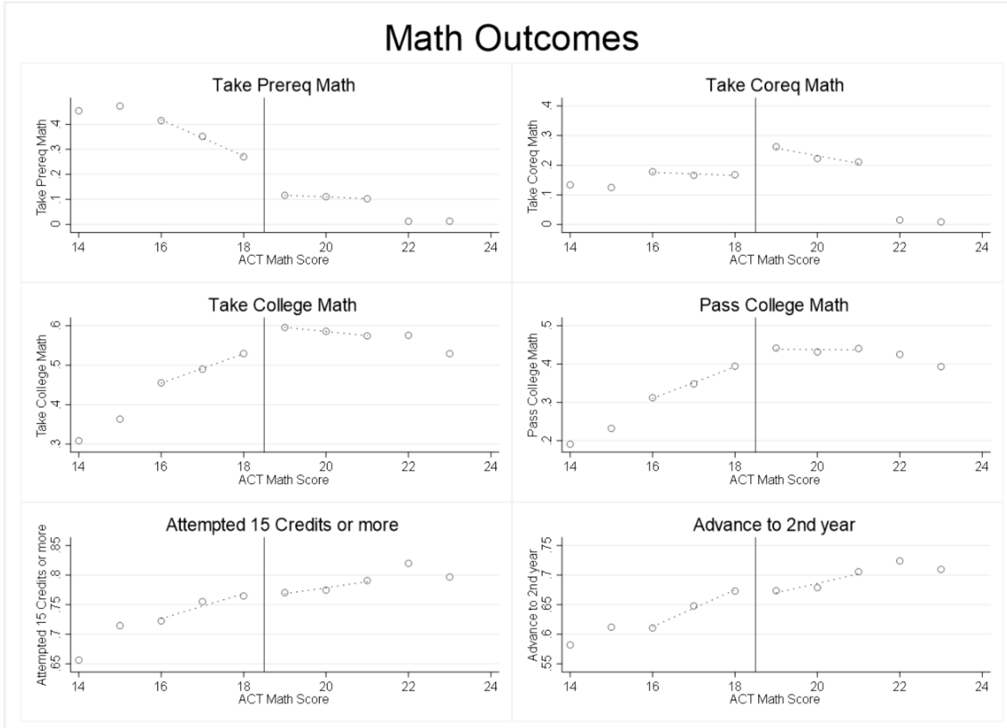
Notes: Year refers to the spring year of a school year. For example, 2017 represents the 2016–17 school year.

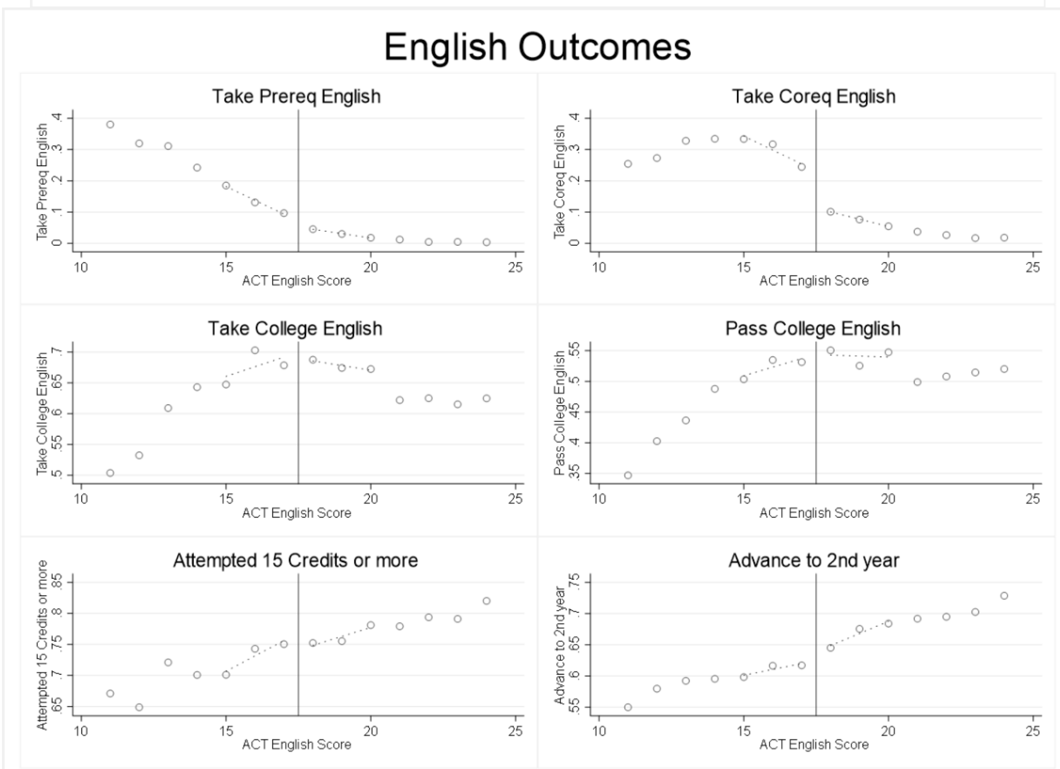
Figure 2. Distribution of ACT and HSGPA Among First-Time Freshmen in KCTCS, 2017–2023



Notes: Dashed vertical lines represent the HSGPA cutoffs (2.8), and dashed horizontal lines represent the ACT cutoffs (19 for math and 18 for English).

Figure 3. Key Math and English Outcomes by ACT Score for Students Whose HSGPA Is 2.8 or Higher

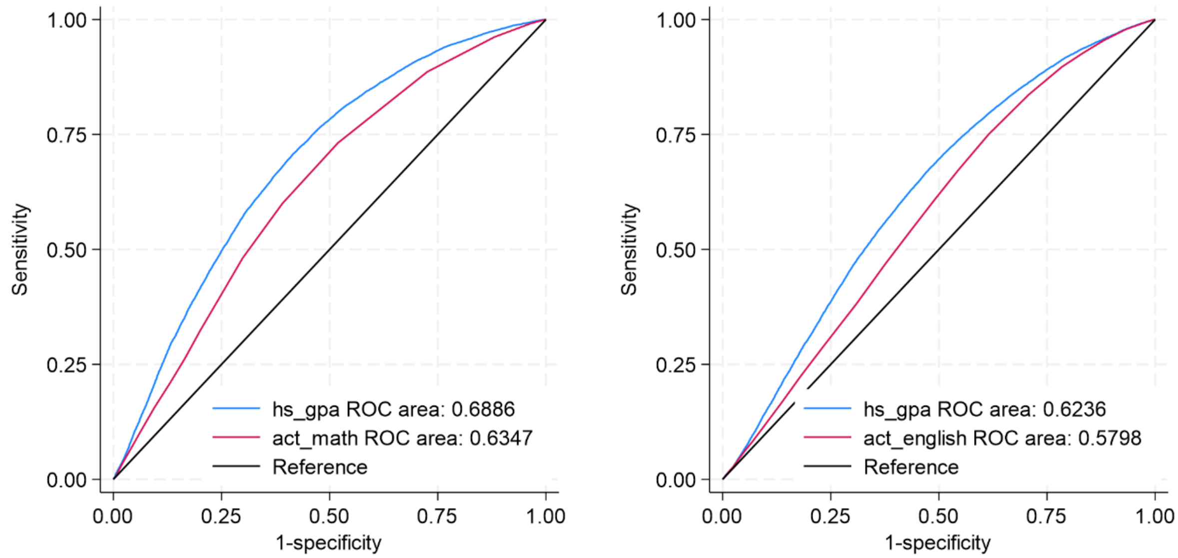




Notes: Displays average outcome by ACT score along with vertical lines denoting college readiness ACT benchmarks of 19 (math) and 18 (English). Each figure contains a linear best fit line through three points on either side of the college readiness cutoffs. Sample includes students from before the HSGPA waiver period whose HSGPA would have qualified them as college ready (i.e., 2.8 and above).

Figure 4. Predictive Power of HSGPA and ACT, by Subject: All Years Combined

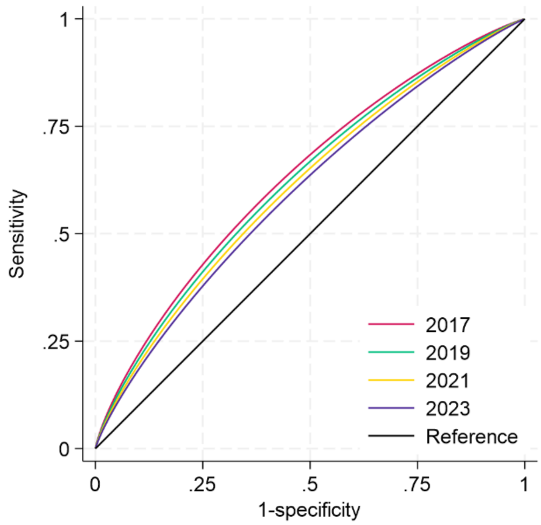
(a) Math (b) English



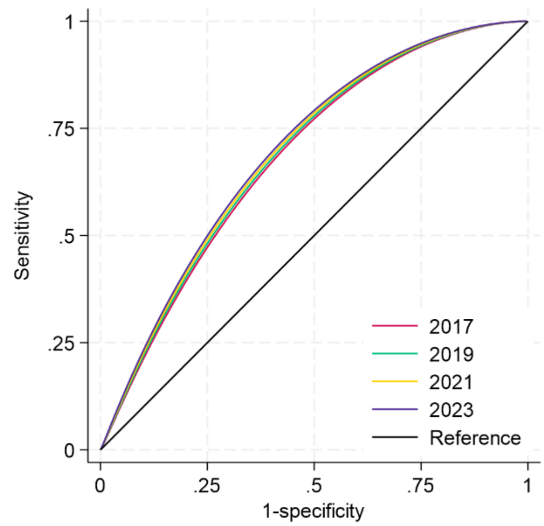
Notes: Passing gatekeeper math and English courses is the outcome of interest. Receiver operating characteristic (ROC) curve plots power (*y*-axis) against type-I errors (*x*-axis) using all possible cutoffs along the distribution of the predictor. The 45-degree reference line suggests prediction that is as good as random. A larger area under the curve (AUC) suggests stronger predictive power.

Figure 5. Change in Predictive Power Over Time for HSGPA and ACT Score

(a) Math

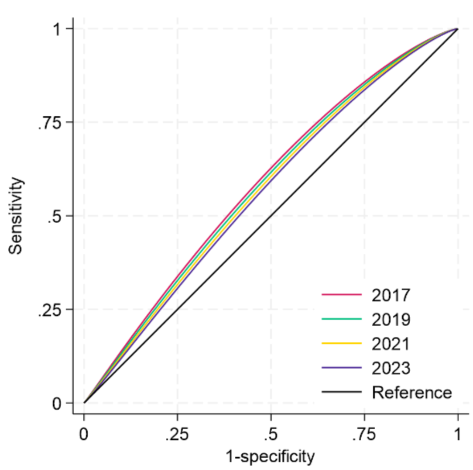


ACT score

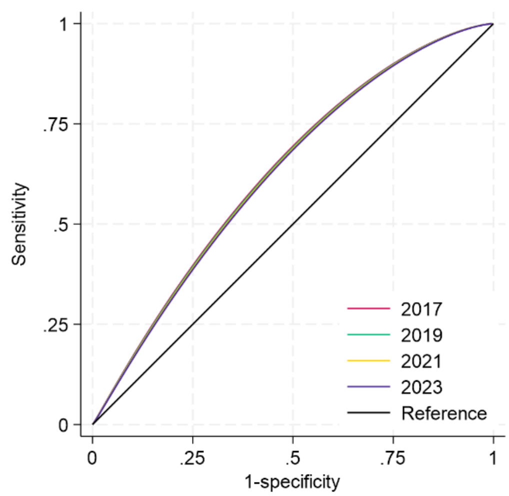


HSGPA

(b) English



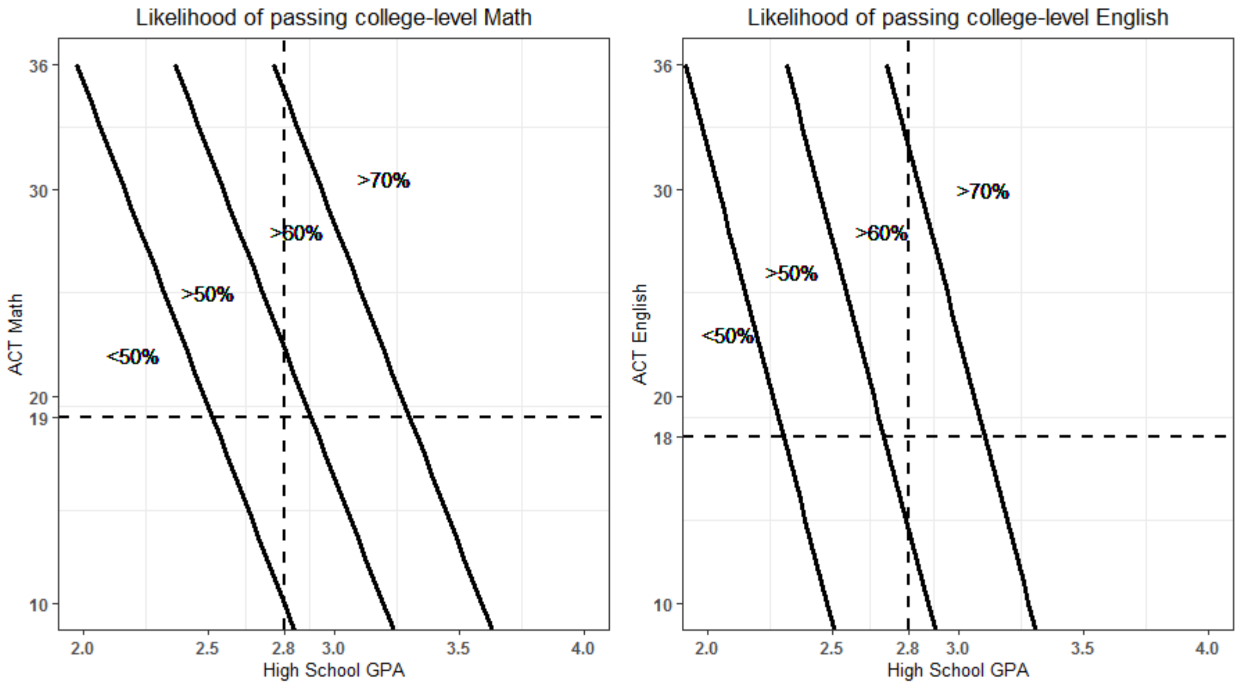
ACT score



HSGPA

Notes: Passing gatekeeper math and English courses is the outcome of interest. Receiver operating characteristic (ROC) curve plots power (*y*-axis) against type-I errors (*x*-axis) using all possible cutoffs along the distribution of the predictor. The 45-degree reference line suggests prediction that is as good as random. A larger area under the curve (AUC) suggests stronger predictive power.

Figure 6. Overlaps of Predicted College-Ready Students Under the KCTCS Waiver Policy and Under an Aggregate MMA



Notes: Points on each isoquant represent all combinations of HSGPA and ACT scores that have the same predicted success rate. The slopes of the lines are -31.4 in math and -45.9 in ELA. To understand the relative importance of HSGPA and ACT subject scores, we to convert these measures into comparable standard deviation units. The standard deviations for HSGPA, ACT math, and ACT English are 0.63, 3.63, and 5.09, respectively. After the conversion, HSGPA receives about 5.4 times as much weight as ACT scores do for math and 5.7 times as much weight as ACT scores do for English.

Appendix Tables and Figures

Table A1. KCTCS Assessment and Placement Policy

ACT	HSGPA	Pathway / label	Highest courses (with and without supplemental support) 2016-17 ~ 2017-18	2018-19	2019-20 ~ current
Mathematics					
22	3.0	CA ready	MAT150	MAT161	MAT161
19	2.8	CA corequisite, QR ready	MAT150 + s, MAT146	MAT161 + s, MAT146, STA151	MAT150 + s, MAT146, STA151, PHI250
18	2.8	CA developmental	MAT126 + s, MAT85	MAT161/STA151 + s, MAT85	MAT116
17			MAT116 + s	MAT116 + s	
16	2.2	QR corequisite /developmental	MAT75	MAT75	MAT146 + s, MAT75
14	1.0	Meta-major corequisite /developmental	Pre-algebra domain	Pre-albegra domain	MAT161 + s, STA151 + s, MAT62
English					
18	2.8	College ready	ENG101	ENG101	ENG101
14	2.2	Corequisite /Developmental	ENC91	ENC91	ENC91
12	<2.2	Developmental	ENC90	ENC90	ENC90, IRW85

Notes: "+s" indicates a paired corequisite course.

Table A2. Two-by-Two Contingency Table

	Actual	
	Fail gateway course	Pass gateway course
Not college ready	**True positive (TP)** *8.0 % (Math)* *6.5% (English)*	**False positive (FP)** *6.2% (Math)* *4.8% (English)*
College ready	**False negative (FN)** *24.7% (Math)* *22.6% (English)*	**True negative (TN)** *61%(Math)* *66.2% (English)*
	Sensitivity **TP/(TP+FN)** *0.25 (Math)* *0.22 (English)*	**Specificity** **TN/(TN+FP)** *0.91 (Math)* *0.93 (English)*

Notes: Numbers in italics represent the percentage of students in the study sample who fell into a category defined by the cell. For example, 61% of students in the sample were deemed college ready in math and later passed gateway math during the first year in college.

Table A3. Regression Discontinuity Estimates of Impact of Being Just Below College Ready Among Students in Bump-Up Zone Prior to Policy Change, Bandwidth 2

	Take Prereq Course	Take Coreq Course	Take Gateway Course	Pass Gateway Course	15 or more credits	Advance to 2nd Year
Math						
Below ACT (All)	0.07***	-0.09***	-0.03	0.00	0.01	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Below ACT (URM)	0.09	-0.06	-0.06	0.04	-0.02	0.01
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)
Below ACT (non-URM)	0.07***	-0.09***	-0.02	-0.00	0.01	0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
English						
Below ACT (All)	0.02	0.07***	-0.03	-0.01	0.01	-0.03
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Below ACT (URM)	-0.01	0.03	-0.06	-0.10	-0.13	-0.07
	(0.05)	(0.07)	(0.08)	(0.09)	(0.08)	(0.09)
Below ACT (non-URM)	0.02	0.08***	-0.03	0.00	0.03	-0.03
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)

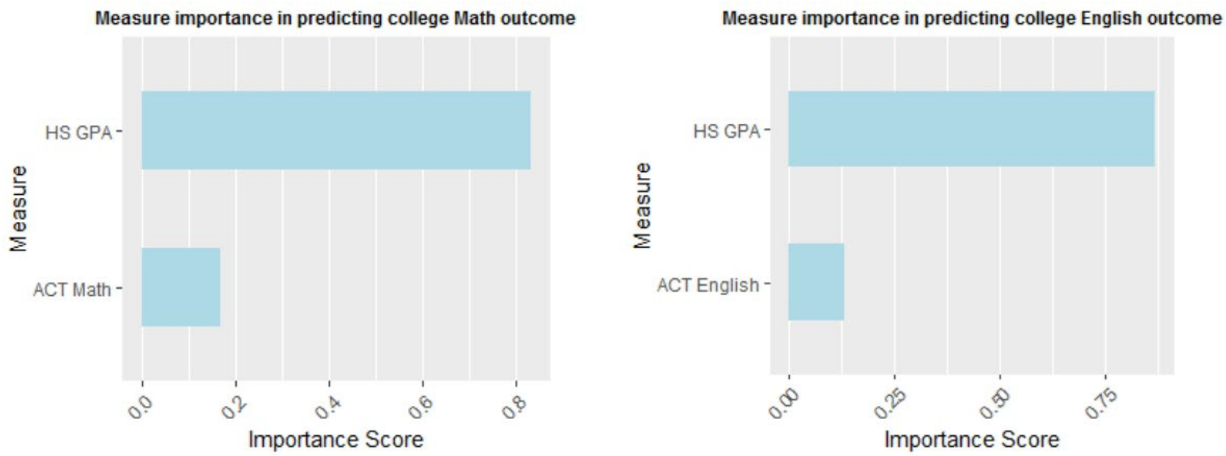
Notes: Each cell displays coefficient estimate from a regression discontinuity design regressing outcome denoted in column header on ACT scores, an indicator for being below the ACT college readiness benchmark, and an interaction between ACT scores and being below benchmark. Coefficients represent the estimated change associated with falling just below college readiness benchmarks among a sample of students whose GPA would have classified them as college ready if the GPA placement policy had been in place when they enrolled. For Math, ACT math is the running variable with a cutoff of 19, and for English, ACT English with a cutoff of 18. Bandwidth is set at 3. The model is estimated parametrically because of the discrete nature of ACT scores. Heteroskedasticity robust standard errors are used to calculate confidence intervals. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

Table A4. Regression Discontinuity Estimates of Impact of Being Just Below College Ready Among Students in Bump-Up Zone Prior to Policy Change, Bandwidth 4

	Take Prereq Course	Take Coreq Course	Take Gateway Course	Pass Gateway Course	15 or more credits	Advance to 2nd Year
Math						
Below ACT (All)	0.08***	-0.10***	-0.01	0.00	0.02	0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Below ACT (URM)	0.12***	-0.12***	-0.04	-0.01	-0.06	-0.04
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)
Below ACT (non-URM)	0.07***	-0.10***	-0.01	0.01	0.02*	0.03*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
English						
Below ACT (All)	-0.00	0.14***	0.02	0.01	0.02	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Below ACT (URM)	-0.06	0.16***	0.04	0.02	0.01	-0.05
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
Below ACT (non-URM)	0.01	0.14***	0.02	0.00	0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)

Notes: Each cell displays coefficient estimate from a regression discontinuity design regressing outcome denoted in column header on ACT scores, an indicator for being below the ACT college readiness benchmark, and an interaction between ACT scores and being below benchmark. Coefficients represent the estimated change associated with falling just below college readiness benchmarks among a sample of students whose GPA would have classified them as college ready if the GPA placement policy had been in place when they enrolled. For Math, ACT math is the running variable with a cutoff of 19, and for English, ACT English with cutoff of 18. Bandwidth is set at 3. The model is estimated parametrically because of the discrete nature of ACT scores. Heteroskedasticity robust standard errors are used to calculate confidence intervals. The symbols *, **, *** represent statistical significance at 10%, 5%, and 1%, respectively.

Figure A1. Variable Importance From XGBoost



(a) Math **(b) English**

Notes: Variable importance from prediction of passing college-level math or English course.