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Removing Barriers to College Credits: Where and for Whom AP Exam Fee Waivers Work

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Do policies that broaden educational access also foster success? We study this question in the context of North Carolina's universal Advanced Placement (AP) exam fee waiver policy. Using student-course level administrative data, we exploit within-student variation on a sample of students who took multiple AP courses to estimate the policy's effect on exam participation (access) and pass rates (success). We find that fee waivers significantly increased exam participation but had no overall effect on the pass rate for these enrollees. This, however, masks a robust 3 percentage point increase in the pass rates among low-SES students. We also find imprecise but suggestive evidence of gains among underrepresented minorities (non-Asian and non-White). A complementary analysis, leveraging the full sample of AP courses, shows that fee waivers had the greatest impact in courses where predicted financial barriers to exam participation were highest, and that the policy's benefits far exceed its cost. Finally, our results help reconcile the seemingly disparate findings from prior work on AP exam funding.

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Removing Barriers to College Credits: Where and for Whom AP Exam Fee Waivers Work *†

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Abstract

Do policies that broaden educational access also foster success? We study this question in the context of North Carolina's universal Advanced Placement (AP) exam fee waiver policy. Using student-course level administrative data, we exploit within-student variation on a sample of students who took multiple AP courses to estimate the policy's effect on exam participation (access) and pass rates (success). We find that fee waivers significantly increased exam participation but had no overall effect on the pass rate for these enrollees. This, however, masks a robust 3 percentage point increase in the pass rates among low-SES students. We also find imprecise but suggestive evidence of gains among underrepresented minorities (non-Asian and non-White). A complementary analysis, leveraging the full sample of AP courses, shows that fee waivers had the greatest impact in courses where predicted financial barriers to exam participation were highest, and that the policy's benefits far exceed its cost. Finally, our results help reconcile the seemingly disparate findings from prior work on AP exam funding.

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A bachelor's degree demonstrably improves earnings and is a key driver of upward mobility (Bailey & Dynarski, 2011; Barrow & Malamud, 2015; Cheah et al., 2021). However, nearly 20 percent students drop out of college during the first year and approximately 40 percent take more than four years to graduate (National Center for Education Statistics, 2022). In response to these challenges, interest has grown in college preparatory programs like Advanced Placement (AP) courses, which offer high school students college-level coursework and the opportunity to earn college credits by achieving a passing score (3 or higher) on standardized AP exams.

Passing AP exams significantly improves on-time college completion (Jackson, 2014; Smith et al., 2017).[1] Yet, more than one in four AP enrollees do not take the standardized exams, despite evidence suggesting that up to one-third of these untaken exams would have resulted in scores eligible for college credit (Fazlul et al., 2021; Kim-Christian & McDermott, 2022).

Subsidies for AP exam fees (which cost $98 in 2024) significantly increase exam participation, particularly among low-income and minority groups (Callen & Stoddard, 2024; Fazlul et al., 2021).[2] While the federal government has long been subsidized a significant part of the fee for low-income students, several states and local school districts have independently implemented policies to subsidize fees for all or targeted student groups (Fazlul et al., 2021). As of 2024, 19 states and the District of Columbia fully cover AP exam costs for low-income students. Among this group, 6 states provide universal fee waivers to all public school students, regardless of income (Callen & Stoddard, 2024; Zinth, 2016).[3] However, evidence on the extent to which AP exam funding affects college credit attainment remains scant.

[1] Evidence further suggests that AP scores significantly influence students' choice of college major (Avery et al., 2018), with receipt of college credits conditional on a passing score not only increasing STEM coursework but also reducing the gender gap in STEM participation by half (Gurantz, 2021). Additionally, AP credits also increase probability of college completion and labor market earnings over the long run (Jackson, 2010, 2014). In contrast, AP expansions, primarily increasing course enrollment and exam taking, have an ambiguous effect on college enrollment and persistence (Beard et al., 2019; Conger et al., 2023; Klopfenstein & Thomas, 2009; Owen, 2024).

[2] Research has also shown that students respond strongly to small costs in the context of college application fees (Smith et al., 2015), extending support that AP exam fees may be a substantial barrier to exam participation.

[3] The 6 states are Arkansas, Florida, Kentucky, North Carolina, South Carolina, and Tennessee. Also see "Federal and State AP Exam Fee Assistance".
Available: https://apcentral.collegeboard.org/exam-administration-ordering-scores/ordering-fees/exam-fees/federal-state-assistance [Accessed 06.09.2025]

In this paper, we link student-course level transcript records from North Carolina to College Board's AP exam data to estimate the effect of universal AP exam fee waivers on exam participation (access) and college credit attainment (success). Leveraging a panel of students who took AP courses both before and after the policy implementation in 2014-15 school-year (SY), we estimate Individual Fixed Effects (IFE) models. We find that fee waivers increased exam participation by approximately 2.1 percentage points, but had no significant effect on the probability of a course leading to a 3 or higher exam score, typically eligible for college credit. We further document sizable narrowing of exam participation gaps across socioeconomic and ethnic student groups as well as across AP subjects.[4] We provide robust evidence of a 15% reduction in the potential college-credit attainment gap between AP students of low- and high-socioeconomic status (SES). While we also find suggestive evidence of gains among underrepresented minorities (non-Asian and non-White) and in underutilized AP courses (defined by below-median pre-waiver exam participation), our estimates are imprecise.

Our IFE estimates may be attenuated by pre-existing local AP exam funding policies. Furthermore, students who enroll in multiple AP courses may be fundamentally different from the general AP population, limiting the generalizability of these estimates. Indeed, the pre-waiver exam participation rate was approximately 90% among multiple AP course takers, significantly greater than the rate (∼80%) among the broader AP population. Therefore, to provide a more generalizable result, we employ an algorithm-driven difference-in-differences (DD) design on our full sample of AP courses. This approach allows us to investigate whether the fee waivers had a greater impact on courses where ex-ante financial barriers were most pronounced.

Our DD framework leverages a two-stage design. In the first stage, we predict the probability of each course resulting in an exam in the absence of fee waivers,[5] and then split our entire sample of AP courses into low- and high-exam-taking-propensity groups at arbitrary percentile thresholds (e.g., the 25th, 50th, or 75th percentile), based on the pre-waiver distribution of predicted probabilities. In the second stage, we estimate the

[4] In this paper, "course" refers to a specific class enrollment, while "subject" refers to the broader academic discipline (e.g., AP Calculus, AP US History).

[5] We do this by training and cross-validating several predictive models on pre-waiver data and select the best model using Area Under the Receiver Operating Characteristic Curve (AUC-ROC) as our model selection metric. The details of our model choice is discussed in Appendix A.

effect of the fee waivers on exam participation and passing by comparing the outcomes between the low- and high-propensity courses.

We find that exam participation in low-propensity courses—defined as those with predicted exam-taking propensity below the pre-waiver median threshold—increased by roughly 17 percentage points relative to high-propensity courses. Moreover, approximately 30% of the additional exams induced by the waiver resulted in passing scores. We further show that the effect on both exam participation and passing steadily increases as we lower the threshold for defining low-propensity courses from the 90th to the 10th percentile of the pre-waiver propensity distribution, implying that the waiver's effects were most concentrated in courses facing high ex-ante barriers to exam participation. We present strong evidence supporting the parallel trends assumption in standard cases.

Our data and identification strategies have two key advantages. First, our within-student identification strategy mitigates compositional bias arising from potential shifts in the underlying distribution of AP student ability/motivation or from student sorting across AP courses induced by the fee waivers.[6] For example, the introduction of fee waivers may induce students with relatively lower ability or motivation to enroll in AP courses, which in theory is likely to attenuate the estimated effect for pass rate. That is, if individual heterogeneity in ability, prior academic preparation, and intrinsic motivation are not accounted for, declining pass rates resulting from changes in the composition of potential test-takers may be deemed as evidence that the waivers are ineffective for increasing pass rate. Conversely, the waivers may raise overall pass rate by inducing positive selection, for example by encouraging high-ability students to enroll in more AP courses or by causing a general shift towards subjects that are easier to pass. While we report evidence of such compositional changes, our identification strategy is robust to such endogenous compositional changes. The individual fixed effects enable a within-student comparison, holding the student ability/motivation constant. Additionally, our model includes grade, subject, and teacher fixed effects to neutralize potential bias from the non-random sorting of these students into different courses and teachers.

Second, our single-state focus strengthens causal identification by holding the broader

[6] This is also referred to as the 'stationarity' assumption and is violated if the underlying composition of the treated group changes differentially compared to the control group over time (Heckman et al., 1999; Sant'Anna & Xu, 2023).

policy environment constant. This avoids confounding from overlapping policy adoptions—a common challenge in comparative studies (Hoehn-Velasco et al., 2024)—and allows us to disentangle the effect of the fee waivers from other policies, such as AP expansions or integration of AP metrics in school accountability systems (Zinth, 2016).

We contribute to the AP exam funding literature in two ways. First, our findings reconcile the seemingly disparate results from prior research. We find that while waiver-induced exam participants are less proficient on average, many exams left untaken in the absence of a fee waiver would have resulted in a passing score. This supports the findings from the predictive analysis of Fazlul et al. (2021) and highlights a key limitation of relying on aggregate state-level data, which show a significant drop in the overall "pass rate among exam takers" following the introduction of fee waivers (Callen & Stoddard, 2024). We argue that the pass rate among exam takers, which we term "exam pass rate" as opposed to "pass rate", is an imperfect metric for evaluating AP exam funding policies. Focusing on the pass rate among exam-takers rather than the likelihood of an AP course resulting in a passing score may provide a distorted view of the benefits of the AP exam fee waivers.[7]

Second, we assess the policy's efficiency and distributional incidence. We find that the benefits are not uniform, but exhibit significant heterogeneity, concentrating in high-barrier contexts. Applying the Marginal Value of Public Funds (MVPF) framework, we quantify this efficiency: every $1 of public spending returns $2.11 of benefits to low-SES students and $2.64 of benefits to students in courses with the highest predicted financial barriers (Hendren & Sprung-Keyser, 2020). Our results demonstrate that while universal fee waivers may have a muted average effect for high-achieving, multiple-course takers, they still generate significant value for the most vulnerable target population.

This paper is organized as follows. Section 1 and 2 describe the policy context and

[7] For instance, imagine an AP class with 10 students. Without access to the fee waivers, 3 do not take the exam, and among 7 exam takers 5 achieve passing scores, leading to an exam pass rate of 71.4% (5 of 7). In a counterfactual world with access to the fee waivers, if 9 (i.e., 2 additional) students take the exam with 6 achieving passing scores, the exam pass rate declines to 66.7% (6/9). However, the decline masks an increase in the percent of enrolled AP students passing the exam, marked by a rise from 50% (5 of 10) to 60% (6 of 10). As such, exam pass rate may lead policymakers to underestimate the benefits of AP exam funding. We note that our results are consistent with the results in Table 7 (Panel B) of Callen and Stoddard (2024), which show a positive, though statistically noisy, estimate of the impact of AP funding on the number of passed exams per 100 high school students.

the data, respectively. Section 3 describes our identification strategies and the effects of the AP exam fee waivers policy across various margins. Finally, section 4 concludes with policy recommendations.

1. Policy Context

North Carolina General Statute 115C-174.26, enacted through Session Law 2013-360, Section 8.27(b), established the state's commitment to expanding access to advanced courses, including coverage of Advanced Placement (AP) exam fees. Although the statute was passed in 2013, appropriations to cover AP exam fees for all North Carolina public school students was not allocated until the 2014-2015 school-year.[8] As a result, starting from 2015, students enrolled in NC public school AP courses can take the corresponding AP exams for free, regardless of the number of different AP exams a student chooses to take.

It is worth noting that the exam fee waivers apply not only to Advanced Placement courses, but also to International Baccalaureate (IB) and Cambridge Advanced International Certificate of Education (AICE) certification courses.[9] We focus on Advanced Placement for two reasons. First, IB or Cambridge AICE exam records are not available in North Carolina Education Research Data Center (NCERDC) data. Second, AP is the most popular college preparatory program in both the U.S. and in North Carolina (College Board, 2023; North Carolina Department of Public Instruction, 2015).

2. Data

We use administrative education records provided by North Carolina Education Research Data Center (NCERDC). Our analysis relies on granular student-course (or enroll-

[8]This is documented in North Carolina Department of Public Instruction (NCDPI) report dated November 15, 2014, which notes, "This school year will be the first year when all students' test and registration fees are covered by NCDPI through the NCAPP legislation... as of this point, no test fees have been allocated" (North Carolina Department of Public Instruction, 2014). A follow-up report issued on November 15, 2015, confirms the successful rollout, referring to the 2014–15 school-year as the "initial implementation year of the state-covered AP exam fees" (North Carolina Department of Public Instruction, 2015).

[9]The Cambridge AICE exams are funded beginning SY 2016-17.

ment) level data. The unit of observation is a student in a specific AP course, meaning each student has a separate observation for every AP course in which they enroll. We refer to this granular data structure as 'course-level' for brevity.

We link the course-level records from student transcripts to the College Board's Advanced Placement exam data in two steps. First, following Fazlul et al. (2021), we restrict the sample to year-long or second semester AP courses. We then link the records to the publicly available master course list for a given school-year. Using an AP course-to-exam code crosswalk, we merge the transcript records with the College Board's AP exam details. To estimate changes in the probability of a student's course resulting in a passing score, we assign a score of 0 to any untaken exam (AP exam scores otherwise range from 1 to 5). We merge course-level records to student demographic characteristics such as race, gender, and socioeconomic status, and prior educational achievement metrics such as standardized eighth-grade math and reading scores.[10] Finally, we match AP courses to their teachers using course membership files.

Our main analysis excludes 23 low-performing school districts that have received a complex bundle of services from the North Carolina Advanced Placement Partnership (NCAPP) since SY 2013-14. These services included teacher training, counseling support, and other administrative assistance in addition to exam fee waivers. Because we are unable to isolate the effects of fee waivers from the other bundled services provided to these districts, we omit them from our analysis. However, we demonstrate that our main findings are robust to the inclusion of these districts in the sample.[11]

Figure 1 plots the annual AP enrollment counts, illustrating the effect of our sample restrictions. The figure compares the full population of enrollments against our analytical sample, which is restricted to second-semester and year-long courses and non-NCAPP target districts. Our final sample consists of 556,514 student-course enrollments from the

[10] The 8th grade math and reading scores are standardized within a given school-year. A full summary of NCERDC data is publicly available at https://childandfamilypolicy.duke.edu/north-carolina-education-research-data/.

[11] We believe that AP enrollees in the 23 school districts targeted by the North Carolina Advanced Placement Partnership (NCAPP) received fee waivers during SY 2013–14, prior to the statewide rollout. The College Board's 2013–14 NCAPP annual report, embedded within the 2014 NCDPI report, notes the Board's collaboration with these districts to improve AP outcomes. This, coupled with the fact that AP exam fees are covered under NCAPP legislation and that exam participation has sharply increased in these districts [see Figure C.1], suggests early access to fee waivers.

2010-11 to 2016-17 academic years.

2.1. Summary Statistics

Table 1 reports the pre- and post-waiver mean outcomes and student characteristics from course-level data for two samples: the full sample, comprised of all year-long or second-semester AP courses from 2011 to 2017, and the multiple AP course-taker sample, henceforth referred to as the "within-student panel", comprised of courses taken by students observed in AP courses in both the pre- and post-waiver periods. We leverage both samples for distinct purposes in our analysis. The within-student panel allows us to estimate the policy's average effect, while we use the full sample to investigate whether the impact of fee waivers was concentrated in courses facing the highest cost barriers.

In the full sample, we observe large changes in the student composition of AP courses after the introduction of fee waivers. Column (1) and (2) of Table 1 highlight that while the concentration of White students in AP courses decreased, there was an increase in AP enrollment for Asian and Hispanic students. AP exam participation increased by roughly 13 percentage points, while the pass rate increased by just 1 percentage point. The average 8th grade math and reading z-scores among AP courses decreased by approximately 0.05 standard deviations, providing suggestive evidence that the share of lower-ability students taking AP courses increased after the fee waivers. However, the average course grade point increased by nearly 0.14 points on a 4-point scale.

Comparing Columns (4) and (5) of Table 1, we observe that the demographic characteristics of multiple AP course-takers across the pre- and post-waiver periods remained stable. However, pre-waiver exam participation among these students was comparatively higher than the full sample, with the pre- to post-period increase in exam participation relatively smaller.

2.2. Descriptive Findings

We document trends in AP exam participation and pass rates in Figure 2, which plots changes relative to 2014 — the year before AP exam funds were first appropriated. Exam participation per 100 AP courses increased by roughly 10 percentage points (from

~80 to ~90 percent) in the initial year of fee waivers and has continued to rise. Equally noteworthy is the pass rate (light blue line), which increased by roughly 2 percentage points and has continued to ascend.

We find that trends in exam participation and pass rates varied substantially based on the specific AP course a student is taking. Figure 3 depicts the exam participation (left) and pass rate (right) per 100 AP courses across 32 subjects, ordered by their pre-waiver participation rates. The left panel reveals significant variation in both pre-waiver exam participation and the subsequent change after fee waivers were implemented. The most notable point is that underutilized courses—those with below-median pre-waiver exam participation, marked by asterisks—experienced the most substantial increases in exam participation on average. These same courses also on-average experienced the largest increases in pass rates, as shown in the right-hand panel of Figure 3.

Figure 4 generalizes the findings of Figure 3, demonstrating a moderate association between the change in exam participation rate and the change in pass rate from the pre- to post-waiver period. A clear pattern emerges: underutilized courses, such as Macroeconomics and French Language, are clustered in the northeast region of the graph. This indicates these courses experienced proportionately larger increases in both participation and pass rates following the waiver. In contrast, the most popular AP courses—indicated by larger circles representing pre-waiver enrollment—saw increases in exam participation that were not matched by comparable gains in pass rates. This suggests that barriers to exam taking (such as financial constraints) may be more binding in underutilized courses, as marginal exam-takers seem to pass these exams more often than marginal exam-takers in more popular courses.

3. The Impact of AP Exam Fee Waivers

We examine the effects of the universal fee waiver policy at various margins. First, using a sample of AP students observed both before and after the waivers, we estimate individual fixed-effects models to identify the average effect by exploiting within-student variation. We then extend this model to estimate equity effects for underserved students. Finally, we examine whether the policy's impact was concentrated among courses facing the highest predicted financial barriers to exam participation. Leveraging the full sample of AP courses and an algorithm-driven difference-in-differences framework, we find evidence that the results from multiple-course enrollees do not generalize. Rather, we provide consistent evidence that exam success improved with the degree of financial barriers faced by an enrollee.[12]

3.1. Average Effects among AP-Enrolled Students

To estimate the average effect of the fee waivers on AP-enrolled students, we exploit within student variation in exam participation and passing. We estimate the following equation using data from the within-student panel, consisting of courses taken by students observed both before and after the introduction of the fee waivers.

$$y_{icgt} = \alpha + \tau \cdot Post_t + \theta_i + \gamma_g + \phi_c + \delta_j + \nu_{icgt} \tag{1}$$

Here, y_{icgt} denotes the outcome for student i enrolled in AP subject c in high school grade g and year t. The outcome variable is either the binary indicator for the AP exam participation or achievement of 3 or higher (passing) score in the exam. θ_i captures the influence of student-specific characteristics that do not vary over time or across courses. We include a rich set of grade, subject, and teacher fixed effects to account for the key sources of bias, such as student progression and sorting. The grade fixed effects (γ_g) and the subject fixed effects (π_c) control for systematic differences in outcomes across grades and AP subjects, ensuring that observed differences in outcomes are not driven by compositional shifts. The teacher fixed effects (δ_j) controls for teacher-specific variation in the outcomes. The policy variable $Post_t$ equals 1 for student i taking AP courses in school-year ending 2015 or later, and equals 0 otherwise. Our coefficient of interest, τ, captures the policy-induced change in the probability of AP exam participation or

[12] We acknowledge that North Carolina's fee waiver was part of a broader initiative that also expanded AP course offerings. While this expansion preceded the fee waiver, we argue it does not bias our main estimates. First, we do not observe a discernible shock to our analysis sample [see Figure 1], suggesting any confounding enrollment effect is likely minimal. Second, our individual fixed-effects specification identifies the policy's effect from within-student changes across AP courses. This strategy controls for time-invariant student heterogeneity, thereby isolating the decision to take the exam from the fixed characteristics that may have driven course enrollment. Finally, our algorithm-driven difference-in-differences results are validated by supportive evidence for parallel pre-trends, lending credence to our causal interpretation.

passing. Finally, ν_{icgt} is the idiosyncratic error term.

The key identifying assumption of our model is that, conditional on the included fixed effects, the timing of the fee waiver's introduction is uncorrelated with any other unobserved, time-varying determinants of a student's exam-taking propensity. While this is not directly testable, we substantiate this assumption in two ways.[13] We first argue that our results align perfectly with economic theory. The fee waiver, a reduction in cost, should primarily affect students on the margin—those with imperfect pre-waiver exam participation—rather than inframarginal students, for whom the cost was not a binding constraint. In Table 2, we show that the growth in exam participation is primarily driven by students with low exam participation rate in the pre-waiver period, providing compelling support that we are capturing a true behavioral response to the policy, rather than a spurious, confounding trend. We also later demonstrate that our findings are robust to broader trends in AP exam difficulty and school quality.

Before discussing the main results, we highlight key pre-to-post-waiver change in outcomes and course-level characteristics in the within-student panel presented in Column 3-6 of Table 1. From Panel B Column 6, we observe a 3.5 percentage point increase in exam taking following the implementation of fee waivers. We also observe a 1.1 percentage point increase in pass rate. We argue that this naive difference may suffer from positive selection or compositional bias, driven by shifts in student sorting among AP-enrolled students. First, fee waivers likely induced higher-ability students to take more AP courses. This is marked by the pre-to-post increase in the number of courses per student and in the course level averages of 8th grade math and reading z-scores. Second, student enrollment grew significantly in underutilized courses after the waiver was introduced. These are also courses that, on average, have high pass rates among exam takers, suggesting they may be easier-to-pass subjects. In the following, we show that our identification strategy, which exploits within-student variation, neutralizes the effects of such endogenous sorting by design.

Table 3 presents the results from estimating various specifications of equation 1 on the

[13] We note that an event study framework may be misleading in this context for two key reasons. First, because our student-course level panel is unbalanced, a dynamic specification of Equation 1 would estimate each lead and lag coefficient using a different, non-random subsample of students, introducing potential compositional bias. Second, isolating the effect of student maturation is infeasible because grade-level progression is severely collinear with calendar year conditional on individual fixed effects.

within-student panel. The baseline model includes individual and high school grade fixed effects in Column 1, and we add subject and teacher fixed effects in successive columns. Panel A shows that the waivers increased AP exam participation. The estimate from our preferred specification in Column 3, including teacher fixed effects, indicates a 2.1 percentage point increase in exam-taking probability. This is roughly half the size of estimates from models without teacher fixed effects, indicating that those specifications likely suffer from omitted variable bias. Our preferred model controls for time-invariant teacher influence on exam-taking, providing a more conservative estimate.

In contrast to the results for exam participation, the estimates in Panel B show a statistically insignificant effect of the fee waiver on the probability that a course results in a passed exam. The point estimates are stable across specifications and centered near zero, indicating a null effect along the student success margin.

In Table C.1, we present evidence that our results are not driven by broader trends in AP subject difficulty or overall school quality. We proxy for these factors using the national annual AP pass rate (among exam takers) by subject and school-level four-year graduation rate, respectively.[14] Adding these controls results in slightly decreased estimates, but does not change the statistical significance.[15]

3.2. Equity Effects among AP-Enrolled Students

To examine whether fee waivers narrow or widen gaps in AP exam taking and passing across subjects and between students with different socioeconomic and ethnic backgrounds, we transform our individual fixed effects model in Equation 1 to a difference-

[14] The subject-level AP pass rates (among exam takers) are drawn from the College Board: https://apstudents.collegeboard.org/about-ap-scores/score-distributions [Accessed: 08-10-2025]. High school graduation rates are calculated from NCERDC 'School Exit' files.

[15] Additionally, approximately 10% of the full within-student sample could not be linked to teachers due to missing teacher identifiers in the course membership files, which, according to NCERDC documentation, are not subject to systematic omission. Our main within-student analyses exclude these observations since we are unable to control for teacher-specific time-invariant factors. As a robustness check, we re-estimate the models on the full within-student sample without teacher fixed effects, and the estimates remain similar to the corresponding specifications [see Table 3 and C.7].

in-differences structure.

$$
\begin{aligned}
y_{icgt} = \alpha \quad &+ \quad \mu \cdot Underserved_{ic} + \beta \cdot Post_t \cdot Underserved_{ic} + \theta_i \\
&+ \quad \gamma_g + \phi_c + \delta_j + \rho_t + \nu_{icgt}
\end{aligned} \tag{2}
$$

Here, we follow the notational conventions established in Equation 1. Additionally, ρ_t denotes year fixed effects,[16] and $Underserved_{ic}$ represents the student i and courses c characteristic defining the group of interest in a given specification. We conduct three separate analyses where $Underserved_{ic}$ is an indicator variable that equals 1, respectively, for low-SES students, minority students, and underutilized courses, and 0 otherwise. The coefficient μ captures the baseline difference between the course group of interest and its comparison set. The coefficient of interest, β, captures the relative effect of the fee waivers on the group of interest.

The validity of these DD estimates relies on the assumption that outcomes between the comparison groups would have evolved similarly absent the fee waivers. Figure 5 largely validates this parallel trends assumption. For most comparisons and considered outcomes, the pre-waiver year coefficients are statistically insignificant. The sole exception is our specification for underrepresented minority (URM) students and the exam participation outcome, for which the 2013 year coefficient is statistically different from zero [see Figure 5(c)]. We argue this is unlikely to be an anticipatory effect, given that state funding for AP exams was not appropriated until 2015. Moreover, a linear approximation of the pre-treatment year coefficients indicates a flat pre-trend, suggesting this single significant point is unlikely to represent a systematic violation of the parallel trends assumption.

We present the results from our DD model in Equation 2 for exam participation and pass outcomes in Table 4(a) and 4(b), respectively. Fee waivers had robust impact on AP exam participation for students in underutilized courses, as well as those from low-SES and minority backgrounds, suggesting that the cost of the exams was a significant barrier for these groups. However, the estimates for the exam passing outcome are unstable

[16] Even though our dataset is an unbalanced course-level panel, in theory, year and high school grade fixed effects are perfectly collinear for a given student. However, we find evidence of non-standard grade progression among a very small number of students (∼1%) in our sample, breaking the perfect collinearity. We also estimated specifications dropping the grade fixed effects. The estimates remain identical.

across specifications.

Panel A Column 3 of 4(b) shows a positive but imprecise estimate for underutilized courses. We note that a separate teacher bonus policy may have attenuated the effect of the fee waivers on underutilized courses (Rahman & Callen, 2025).[17] This is supported by our estimates in Table C.3, where we exclude the years with an active teacher bonus policy. In Panel B Column 3, we find a 3.3 percentage point increase in the pass rate for courses taken by low-SES students relative to high-SES students. This is robust and insensitive to sample changes [see Table C.3 and C.5]. Finally, for courses taken by minority students, we find a positive but insignificant gain in pass rate.

We further note that the positive estimates on pass rates for underserved groups are not driven by a decline in their respective comparison group and can be interpreted as heterogeneous effects of the waivers on pass rates. We document this by estimating a modified version of Equation 2, where we replace the year fixed effects (ρ_t) with a $Post_t$ dummy. In this model, the coefficient on $Post_t$ estimates the fee waivers' average effect and the DD interaction captures the additional effect on the group of interest. Table C.6(b) shows that, for pass rate, the $Post_t$ coefficient estimates are consistently close to zero and the DD coefficients are identical to those estimated from model 2. Furthermore, the sum of the Post coefficient and the DD interaction coefficient represents the effect on the underserved group under consideration.

3.3. Heterogeneity by Exam-Taking Propensity (Full Sample)

Our within-student analyses are based on a sample of AP courses taken by students observed both in the pre- and post-waiver periods. These students had significantly higher pre-waiver exam participation rate (∼90%) compared to the average AP students (∼80%) in North Carolina. Hence, the results are likely less generalizable.

Moreover, our estimates from the within-student panel likely represent a lower bound on the true effect of the fee waivers. It is plausible that some districts had pre-existing, unobserved policies that subsidized AP exams, a practice that is common but rarely

[17]Interestingly, for these same courses we observe a countervailing negative effect within the NCAPP target school districts [see Table C.5(b) Panel A]. A plausible mechanism is an influx of new, inexperienced teachers into these subjects following new teacher training initiatives. However, because these districts received a bundle of unobserved services, we cannot identify the cause.

publicly documented (Fazlul et al., 2021). Such policies would increase the baseline rate of exam participation in those areas, creating a ceiling effect that would mechanically dampen the measured impact of the new statewide universal waiver.

We partially overcome these limitations by testing whether the waiver's effects are concentrated in courses facing the greatest financial barriers.[18] We use a data-driven design that proceeds in the following steps:

1. *Predict exam-taking propensity.-* We first predict the probability that a taken course results in exam participation in the absence of the universal fee waiver.[19] This creates our proxy for the financial barrier faced by students in each course.

2. *Stratify the sample.-* We then split the full sample of AP courses into "low-propensity" and "high-propensity" groups, based on arbitrary percentile thresholds from the pre-waiver distribution of predicted exam-taking probabilities [see Figure 6 for reference]. We test the sensitivity of our results by defining this split at several thresholds (e.g., the 25th, 50th, and 75th percentiles).

3. *Estimate the differential effect.-* Lastly, we estimate the effect of the fee waivers on the low-propensity courses relative to the high-propensity courses using the following difference-in-differences model:

$$y_{icgst} = \alpha + \beta \cdot Post_t \cdot LowPropensity_{icsgt} + \lambda \mathbf{X}_{icgst} + \gamma_g + \phi_c + \delta_s + \rho_t + \nu_{icgst} \quad (3)$$

[18] A naive comparison of courses taken by low- and high-SES students may be confounded by endogenous selection. For example, fee waivers may shift the ability composition of low-SES students taking AP courses in ways that differ from high-SES students, undermining the validity of a direct comparison between the two groups. We also find evidence that pre-waiver exam participation trend differs across these groups. On the other hand, our best predictive model—discussed in Appendix A—identifies certain school district indicators as strong predictors of exam participation [see Figure A.2]. This lends support to the hypothesis that unobserved district-level policies or characteristics were driving participation rates absent the fee waivers.

[19] We do this by training and cross-validating standard prediction models—Logistic regression (Logit), Random Forests (RF), and eXtreme Gradient Boosting (XGBoost)—on pre-waiver data, with features including student demographics (e.g., sex, race, and low-income status), and binary indicators for each AP courses, high school grades, and school districts. Using our best-performing model (XGBoost) coefficients, we then predict exam taking probabilities of all AP courses in our sample. We use Area Under the Receiver Operating Characteristic Curve (AUC-ROC) as our model selection metric, and compare false negative rates across demographic groups to evaluate algorithmic discrimination. The details of our model choice is discussed in Appendix A. Finally, we use our best model to predict exam-taking propensities for all course-level observations.

Where, notational convention is preserved from Equation 2, with the following differences: s denotes schools, and δ_s captures permanent outcome differences across schools. $LowPropensity_{icgst} = \mathbf{1}(Pr[Take = 1] < p_\kappa)$ is a binary variable taking a value of 1 if predicted exam taking probability for course c taken by student i in grade g school s over year t is below the κ^{th} percentile of the pre-waiver predicted probabilities, and 0 otherwise. $\mathbf{X}_{icgst}$ is a vector of covariates, including student demographic variables (sex, race, socioeconomic status, and disability status) and prior academic achievement (standardized 8th grade math and reading scores). The grade (γ_g), course (ϕ_c), and time (ρ_t) fixed effects are defined analogously to those in Equation 2.

The validity of our algorithm-driven difference-in-differences model relies on two key assumptions. First is the standard parallel trends assumption, requiring that outcomes for low- and high-propensity courses would have followed similar time path absent the waivers. Second is the assumption that the composition of student characteristics between the two groups of courses evolved in a similar manner over time.

Table 5 compares pre- and post-waiver characteristics for courses stratified by their predicted exam-taking propensity. For brevity, we present the results for the median (50th percentile) threshold. The table shows strong evidence of compositional stability, except for prior academic achievement — 8th grade average math and reading scores in the low-propensity group decreased relatively more from the pre- to post-waiver period. In theory, this should only attenuate our estimates.

Next, we estimate event study coefficients by modifying Equation 3 and plot them in Figure 7 for three standard percentile thresholds: $\kappa = \{25, 50, 75\}$ in panel (a), (b), and (c), respectively. The plots provide strong evidence supporting the parallel trends assumption, showing a horizontal evolution leading up to the introduction of the waivers. Importantly, we observe an abrupt increase in both exam participation (left) and pass rates (right) that coincides exactly with the first year of the fee waiver. This timing of sharp jumps mitigates concerns that the observed effects are driven by other AP-related policies, which came into effect in different years.

Finally, we report the estimated effects from Model 3 for three alternative definitions of low-propensity courses in Table 6. For courses below the median (50th percentile) of predicted exam-taking probability, we document a >16 percentage point increase in exam participation and >4pp increase in the probability of passing [see column (4)-(6)]. For courses below the 25th (75th) percentile of predicted participation probability, we observe larger (smaller) statistically significant effects on both participation and pass rates [see Columns (1)-(3) and (7)-(9)]. The estimates are robust and stable across different specifications.

It follows from Table 6 that the estimated effects depend on how strictly we define "low-propensity" or "high-barrier" courses. As shown in Figure 8, the impact on both exam participation and passing steadily increases as we lower the threshold for defining low-propensity courses from the 90th to the 10th percentile of the pre-waiver propensity distribution. This indicates that the waivers' effects are most concentrated in courses facing the most significant financial barriers. Overall, for the standard definition of low-propensity courses (those below the median), our estimates suggest an average increase in pass rates of approximately 6%.

4. Concluding Remarks

This study examines a critical question in education policy: do programs that broaden access necessarily promote student success? Our analysis of North Carolina's universal AP exam fee waivers reveals a nuanced answer. While the policy generally increased exam participation, we find no statistically significant increase in college credit attainment for students who took multiple AP courses spanning the pre- and post-waiver periods. However, this null result masks important heterogeneity. The benefits of the waiver are highly concentrated, accruing to low-SES students.

Crucially, our full sample analysis reveals that AP exam fee waivers significantly increase exam participation and pass rates for enrollees who were otherwise unlikely to take the exam. This suggests the universal policy effectively reaches students with unobserved barriers that traditional means-testing cannot not fully capture. While we find that factors like a student's school district and the AP subject are strong predictors of these barriers, targeting subsidies based on such characteristics may be politically and practically infeasible. Therefore, a universal waiver may be the most viable policy instrument for serving this hard-to-identify group of students.

To evaluate the efficacy of the fee waivers, in Appendix B, we use the unified welfare analysis framework of Hendren and Sprung-Keyser (2020) to calculate AP exam fee waiver's Marginal Value of Public Funds (MVPF), which estimates the total returns per $1 spent on the program. The estimated MVPF of $2.11 for low-SES students and $5.28 for students in courses facing high predicted cost barrier to exam participation suggest that public funds spent on AP exam fees generate considerable benefits.

The MVPF estimates permit a direct comparison of policy designs, under the assumption that the estimated pass rate effect for low-SES multiple-course enrollees generalizes to the low-SES AP population. A means-tested policy targeting only low-SES students would yield a $2.11 benefit for every dollar spent in state funds. In contrast, the universal fee waiver, while covering all students, effectively targets high-barrier courses. Since these courses, by design, make up half the sample,[20] the effective return of the universal fee waivers is $2.64 (=$5.28/2) for every dollar of state spending. This suggests that the universal policy is likely more efficient than traditional means-tested fee waiver programs that only provide subsidies to low-income students.

Finally, our findings suggest that funds spent on AP exam fee waivers have wide-ranging benefits for students through the narrowing of access gaps and improved odds of qualifying for college credit. As such, our study contributes to ongoing policy debates around the use of state and federal revenues to fund AP exams. For instance, the North Carolina state senate has proposed eliminating the universal waiver in favor of a means-tested policy targeting only economically disadvantaged students (Patterson, 2025). While our results support the efficacy of fee waivers for low-SES students, they also highlight that targeted waiver programs for coarsely-defined demographic groups may miss many students who stand to benefit from the waivers.

[20]This is because our algorith-driven identification startegy's main estimate on pass rate comes from splitting the sample at the Median of the pre-waiver predicted probability distribution.

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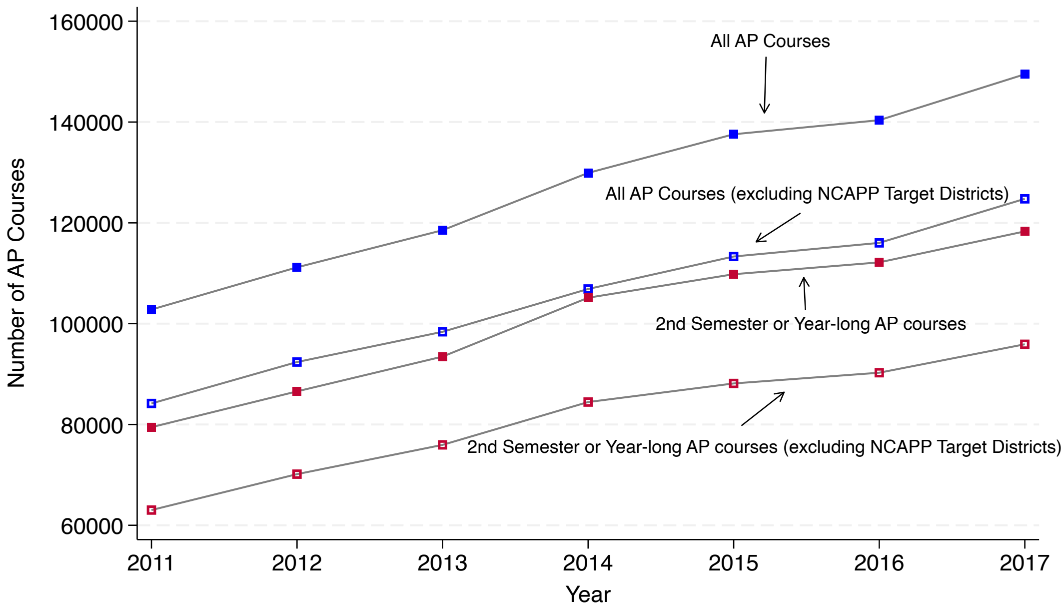
Figure 1: AP Enrollment Trend



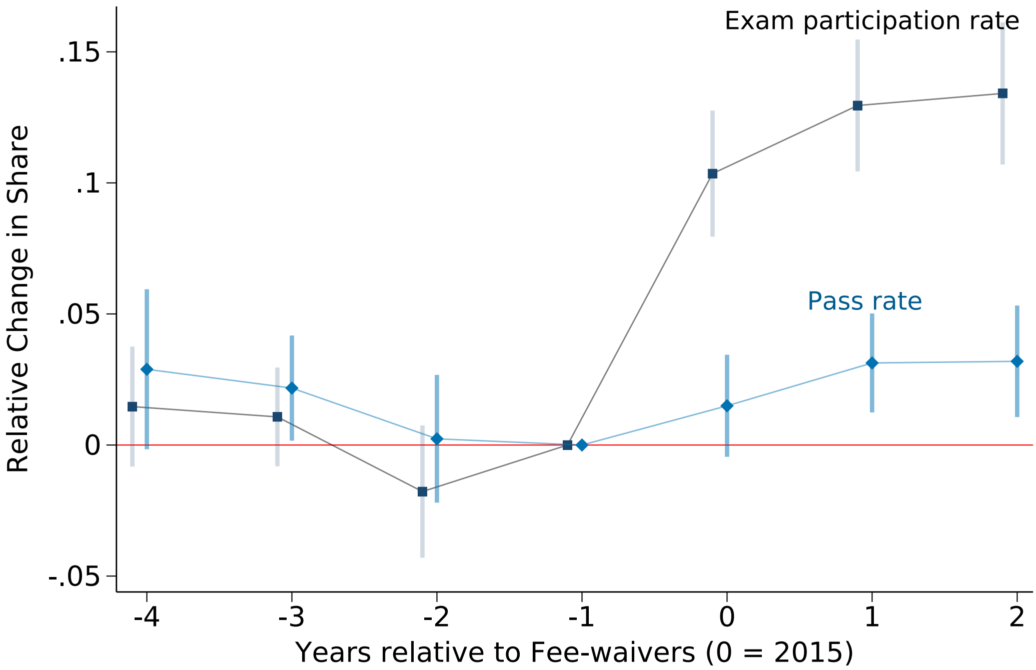
Notes.- This figure plots the AP enrollment trend in North Carolina public schools. Unless otherwise noted, the counts include all first-semester, second-semester, and year-long courses.

Table 1: Summary Statistics

	Full Sample			Within-Student Panel		
	Pre 2011-2014	Post 2015-2017	Difference	Pre 2012-2014	Post 2015-2017	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
A. Demographic Characteristics						
Female	0.559	0.562	0.003(0.001)	0.555	0.547	-0.009(0.003)
Low-SES	0.147	0.143	-0.004(0.001)	0.123	0.103	-0.020(0.002)
Race						
White	0.734	0.709	-0.025(0.001)	0.732	0.722	-0.010(0.003)
Black	0.100	0.100	-0.000(0.001)	0.081	0.080	-0.002(0.002)
Asian	0.073	0.085	0.011(0.001)	0.097	0.109	0.012(0.002)
Hispanic	0.057	0.069	0.012(0.001)	0.049	0.050	0.001(0.001)
Other	0.032	0.033	0.001(0.000)	0.034	0.034	-0.000(0.001)
B. Academic Variables						
Course Grade Point	3.068	3.211	0.143(0.003)	3.230	3.296	0.066(0.006)
Underutilized Courses	0.373	0.320	-0.053(0.001)	0.175	0.420	0.245(0.003)
Exam Participation	0.809	0.931	0.122(0.001)	0.902	0.925	0.023(0.002)
Exam Pass	0.489	0.504	0.014(0.001)	0.574	0.584	0.011(0.003)
Exam Score	2.925	2.737	-0.188(0.004)	3.012	2.990	-0.022(0.009)
8th Grade Math Score	1.093	1.041	-0.053(0.002)	1.180	1.227	0.048(0.005)
8th Grade Reading Score	0.982	0.932	-0.051(0.002)	1.028	1.065	0.036(0.004)
Observations	282,554	273,960		38,000	53,806	
Number of Students	121,148	115,346		20,157	20,157	

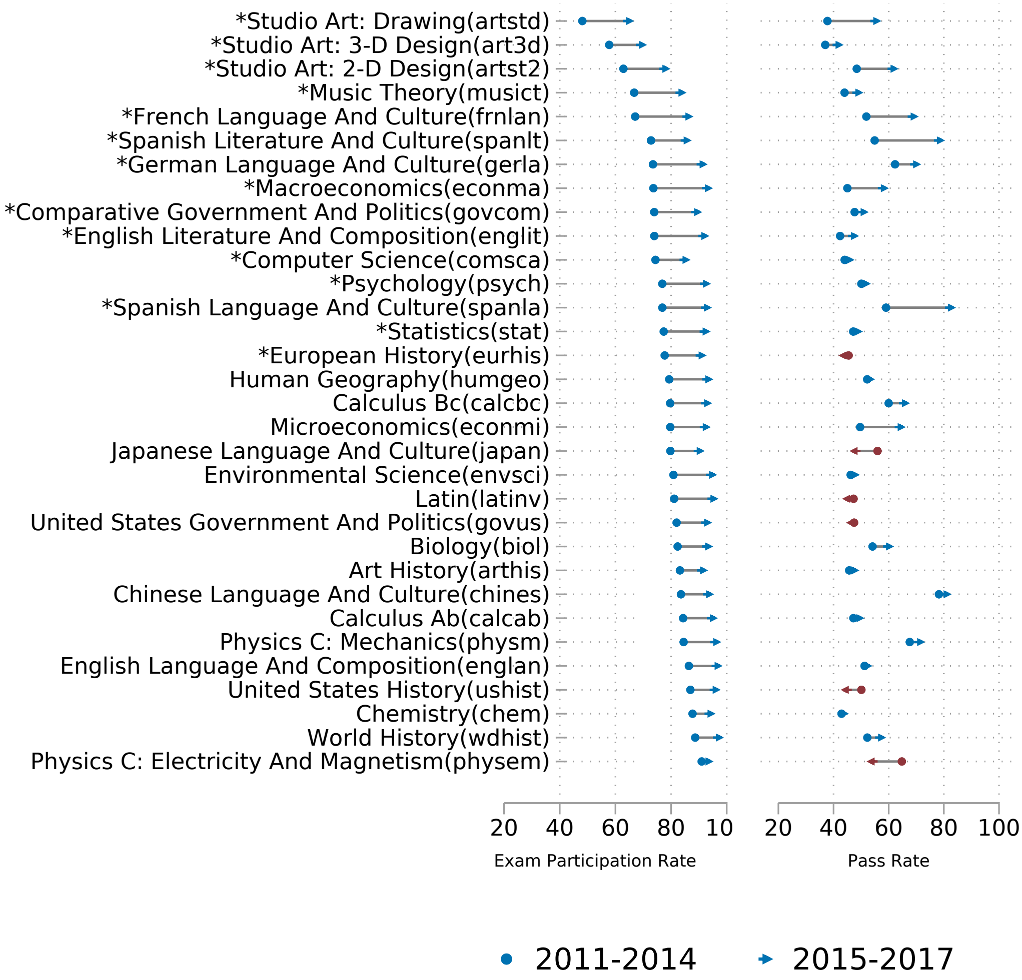
Notes.- This table reports the summary statistics for the key variables using course-level data. The 'Full sample' includes all second semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. The 'within-student panel' is a subset of the 'Full sample', where courses are taken by students observed both before and after the fee waivers are implemented in SY 2014-15. The 8th Grade Math and Reading scores are standardized within year×subject cells.

Figure 2: Trends in AP Exam Participation and Performance



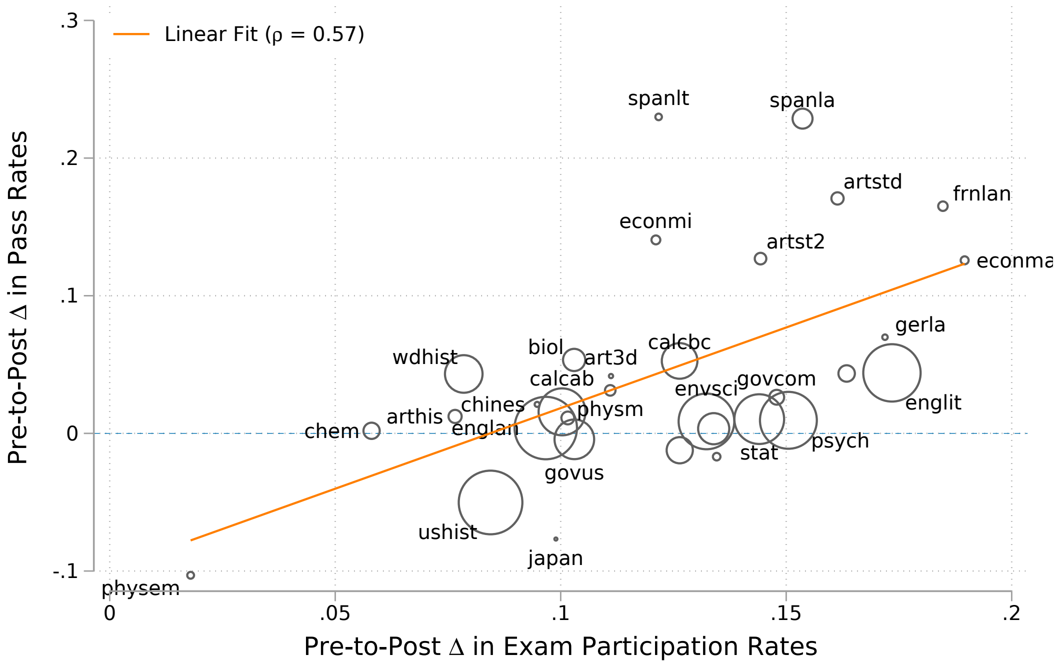
Notes.- The year-coefficients are estimated using Linear Probability model and course-level data including all second-semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. SY 2013-14 (2014) is selected as the base year.

Figure 3: Pre-Post Comparison AP Exam Taking and Pass Rate



Notes.- The pre- and post-waiver means are calculated using course-level data including all second-semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. Additionally, this graph excludes exams observd exclusively before or after the waivers are implemented—specifically, AP Physics 1, AP Physics 2, AP Physics B, Computer Science Principles, and Italian Language and Culture.

Figure 4: Association between Pre-post Changes in Participation and Pass Rates



Notes.- The size of the circles are proportional to the pre-waiver average student enrollment count in the given course. The pre- and post-waiver means are calculated using course-level data including all second-semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. Additionally, this graph excludes exams offered exclusively before or after the waiver period—specifically, AP Physics 1, AP Physics 2, AP Physics B, Computer Science Principles, and Italian Language and Culture.

Table 2: Pre-to-Post Growth, Stratified by Students' Prior Exam Participation Rate

Student Category	Number of	Participation Rate (%)		Pass Rate (%)	
(Based on Pre-Waiver History)	Students	Pre-Waiver	Post-Waiver	Pre-Waiver	Post-Waiver
Perfect (100%)	17,172	100.0	94.6	63.6	61.1
High (>50% to <100%)	541	73.9	83.3	52.2	57.1
Low (≤50%)	2,446	17.9	73.4	8.5	31.4

Notes.- The sample includes high school students who have taken AP courses both before and after the implementation of the AP exam fee waivers in SY 2014-15. The student groups are stratifies by the pre-waiver exam participation rate.

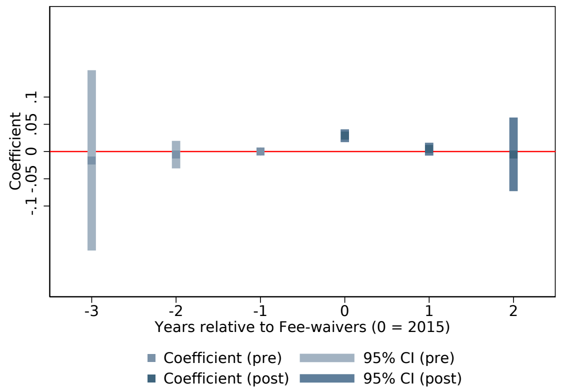
Table 3: Individual Fixed Effects Estimates

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. *Outcome:* Exam Participation			
Post	0.036***	0.036***	0.021***
	(0.004)	(0.004)	(0.004)
Pre-Mean	0.90	0.90	0.90
adj. R^2	0.34	0.34	0.45
B. *Outcome:* Exam Pass			
Post	-0.002	0.006	0.002
	(0.006)	(0.005)	(0.006)
Pre-Mean	0.57	0.57	0.57
adj. R^2	0.41	0.44	0.51
Observations	91,810	91,810	91,810
Number of Students	20,159	20,159	20,159

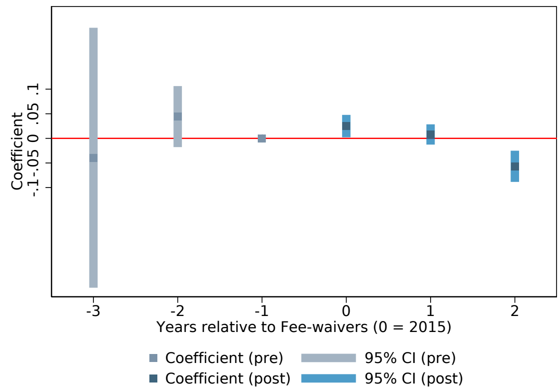
Notes.- All specifications include individual and high school grade fixed effects. Observations are at the course level. The sample includes high school students who have taken AP courses both before and after the implementation of the AP exam fee waivers in SY 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test. The coefficients are estimated using Linear Probability model with standard errors clustered at the individual level.
* p<0.10; ** p<0.05; *** p<0.01

Figure 5: Event Study Estimates for Heterogeneity Analysis

(a) Underutilized vs. High-participation courses

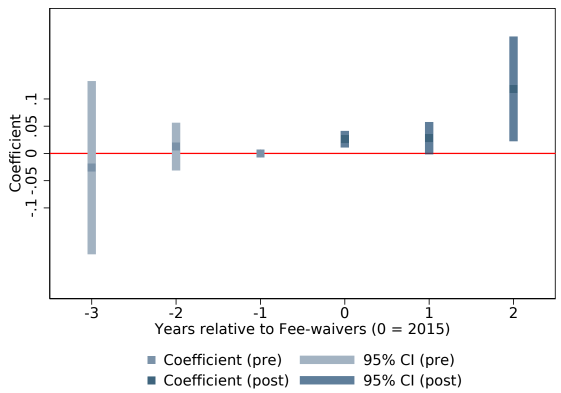


Exam Participation

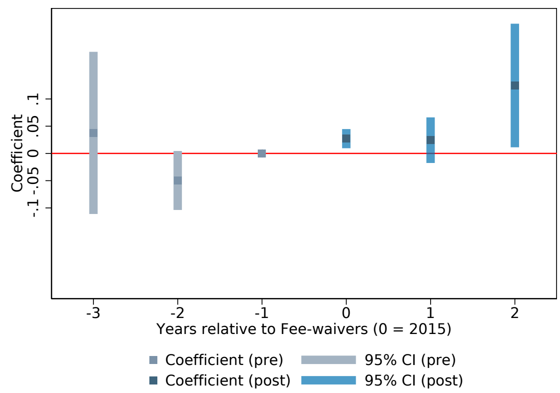


Exam Pass

(b) Low-SES vs. High-SES Students

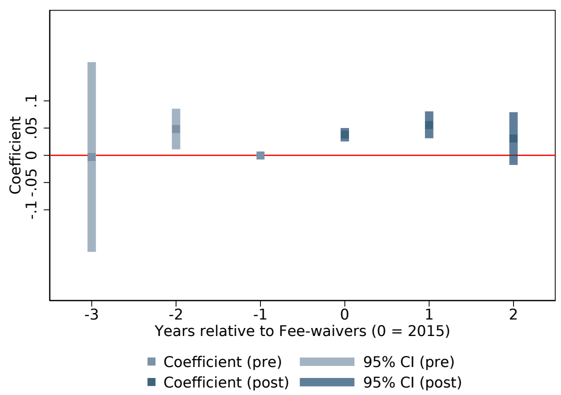


Exam Participation

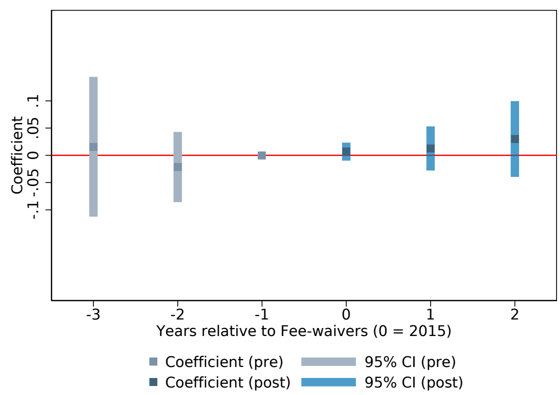


Exam Pass

(c) Underrepresented minority (URM) vs. non-URM students



Exam Participation



Exam Pass

Notes.- Observations are at the course level. The sample includes high school students who have taken AP courses both before and after the implementation of the AP exam fee waivers in SY 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test, except AP Research and Capstone courses. The coefficients are estimated using Linear Probability model. All specifications include individual, high school grade, AP course, and teacher fixed effects.

Table 4: Heterogeneous Effects

(a) Outcome: Exam Participation

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.026***	0.021***	0.022***
	(0.004)	(0.005)	(0.006)
Pre-Mean (Underutilized)	0.90	0.90	0.90
adj. R^2	0.34	0.34	0.46
B. By Student Socioeconomic Status			
Post×Low-SES	0.035***	0.035***	0.026***
	(0.007)	(0.007)	(0.007)
Pre-waiver Mean (Low-SES)	0.86	0.86	0.86
adj. R^2	0.34	0.34	0.46
C. By Student Race/Ethnicity			
Post×URM	0.046***	0.046***	0.035***
	(0.006)	(0.006)	(0.006)
Pre-waiver Mean (URM)	0.84	0.84	0.84
adj. R^2	0.34	0.34	0.45
Observations	91,810	91,810	91,810
Number of Students	20,159	20,159	20,159

Notes.- See Table 3 notes. * p<0.10; ** p<0.05; *** p<0.01

(b) Outcome: Exam Pass

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.041***	0.022***	0.013
	(0.007)	(0.008)	(0.009)
Pre-waiver Mean (Underutilized)	0.62	0.62	0.62
adj. R^2	0.41	0.44	0.51
B. By Student Socioeconomic Status			
Post×Low-SES	0.037***	0.029***	0.033***
	(0.009)	(0.009)	(0.009)
Pre-waiver Mean (Low-SES)	0.36	0.36	0.36
adj. R^2	0.41	0.44	0.51
C. By Student Race/Ethnicity			
Post×URM	0.016**	0.013*	0.010
	(0.007)	(0.007)	(0.008)
Pre-waiver Mean (URM)	0.40	0.40	0.40
adj. R^2	0.41	0.44	0.51
Observations	91,810	91,810	91,810
Number of Students	20,159	20,159	20,159

Figure 6: Density Plot of Predicted Probabilities (Model: XGBoost)

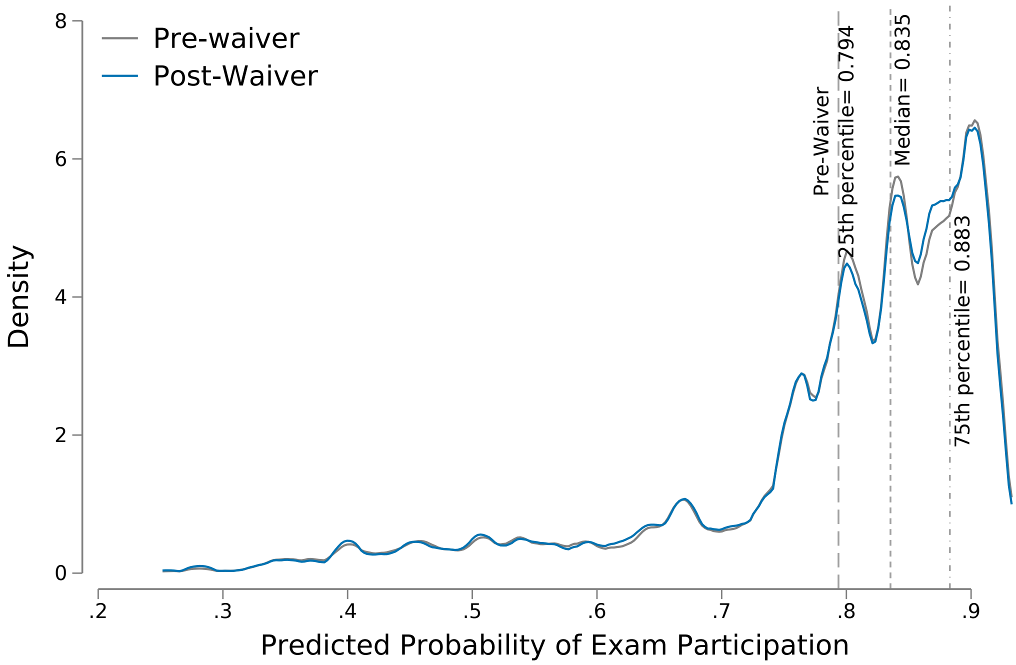


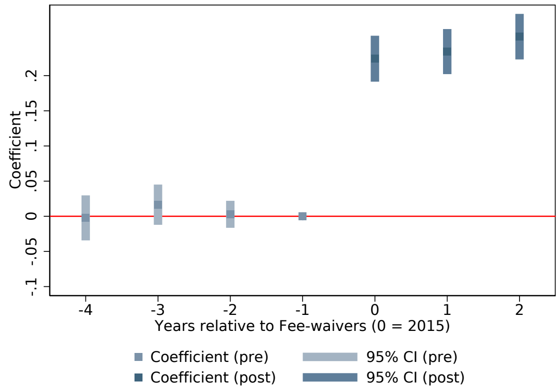
Table 5: Summary Statistics by Predicted Propensity Group

	Threshold: Median (50th Percentile)					
	Low-Propensity			**High-Propensity**		
	Pre 2011-2014	Post 2015-2017	Difference (se)	Pre 2011-2014	Post 2015-2017	Difference (se)
	(1)	(2)	(3)	(4)	(5)	(6)
A. Demographic Characteristics						
Female	0.578	0.584	0.005(0.002)	0.539	0.539	0.000(0.002)
Low-SES	0.188	0.183	-0.005(0.001)	0.106	0.102	-0.004(0.001)
Race						
White	0.678	0.650	-0.028(0.002)	0.790	0.768	-0.022(0.002)
Black	0.147	0.147	0.000(0.001)	0.053	0.053	-0.001(0.001)
Asian	0.067	0.077	0.010(0.001)	0.080	0.092	0.012(0.001)
Hispanic	0.071	0.086	0.015(0.001)	0.042	0.052	0.010(0.001)
Other	0.037	0.040	0.002(0.001)	0.036	0.036	0.000(0.001)
B. Academic Variables						
Course Grade Point	2.901	3.036	0.135(0.004)	3.234	3.385	0.150(0.003)
Underutilized Courses	0.459	0.399	-0.060(0.002)	0.288	0.241	-0.046(0.002)
Exam Participation	0.679	0.888	0.209(0.002)	0.939	0.973	0.035(0.001)
Exam Pass	0.341	0.379	0.039(0.002)	0.638	0.628	-0.010(0.002)
Exam Score	2.615	2.405	-0.210(0.005)	3.150	3.041	-0.109(0.005)
8th Grade Math Score*	0.782	0.704	-0.078(0.003)	1.400	1.378	-0.022(0.002)
8th Grade Reading Score*	0.782	0.704	-0.078(0.002)	1.177	1.158	-0.019(0.002)
Observations	141,244	136,972		141,310	136,988	
Number of Students	76,916	72,058		58,955	54,742	

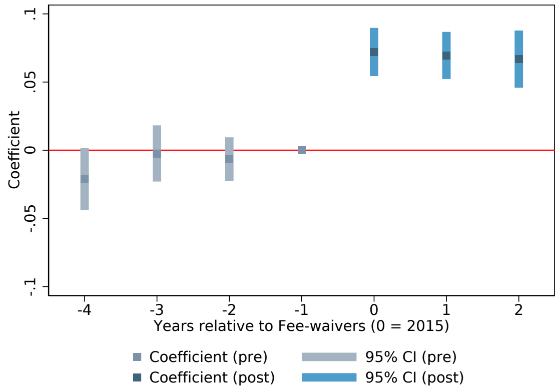
Notes.- This table reports summary statistics for all second semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. Courses are segregated by the 50th percentile predicted probability from the pre-waiver distribution. The 8th Grade Math and Reading scores are standardized within year×subject cells.

Figure 7: Event Study Estimates for Predicted Low-Propensity Courses

(a) Threshold: 25th Percentile (Low-Propensity=$\mathbf{I}(Pr[Take = 1] < p_{25})$)

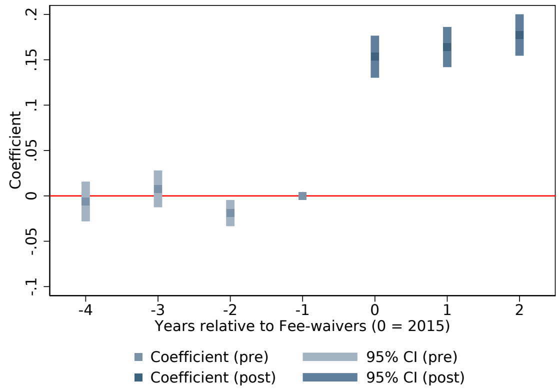


Exam Participation

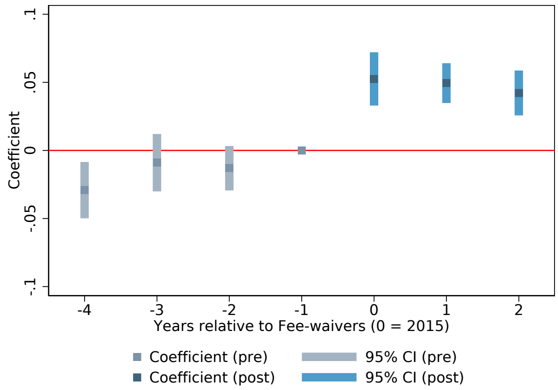


Exam Pass

(b) Threshold: 50th Percentile (Low-Propensity=$\mathbf{I}(Pr[Take = 1] < p_{50})$)

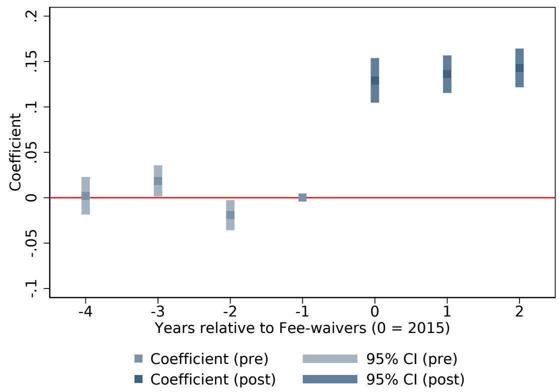


Exam Participation

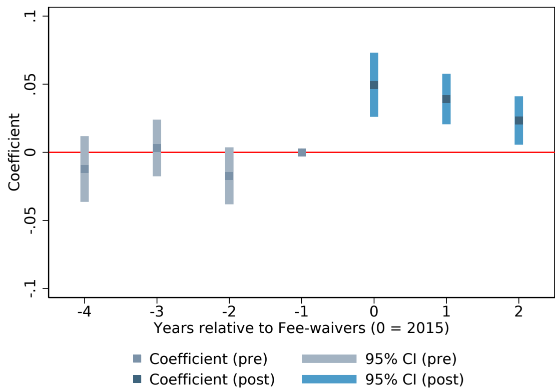


Exam Pass

(c) Threshold: 75th Percentile (Low-Propensity=$\mathbf{I}(Pr[Take = 1] < p_{75})$)



Exam Participation



Exam Pass

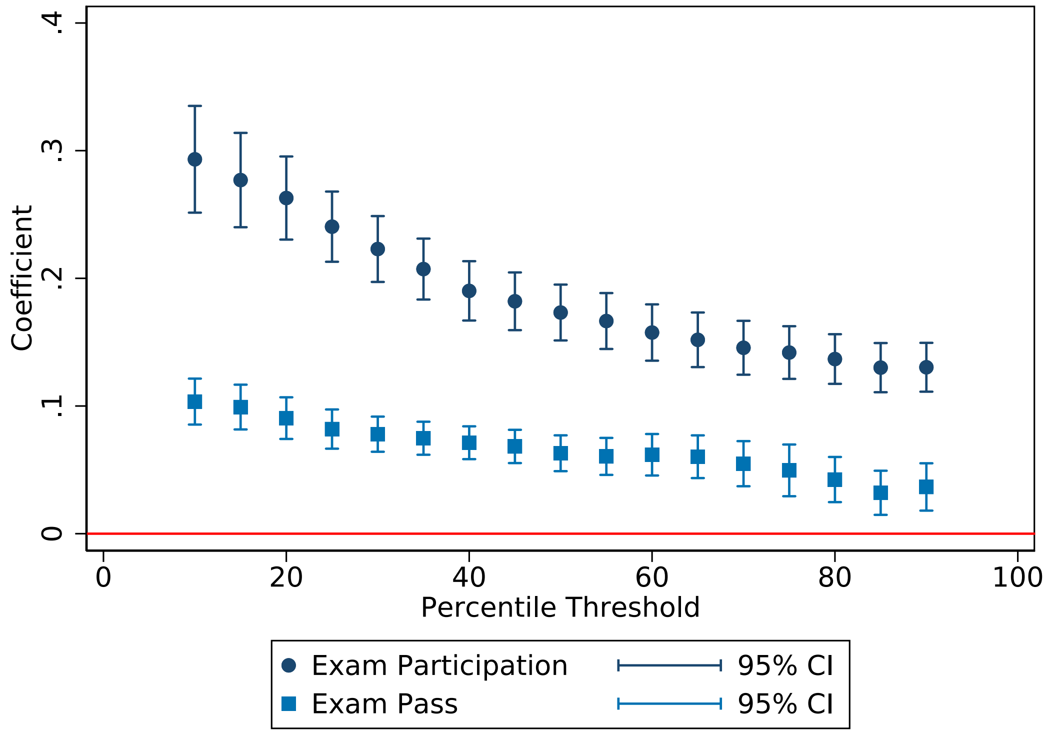
Notes.- See Table 6 notes.

Table 6: Algorithm-driven Difference-in-Differences Estimates

	Threshold: 25th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1] < p_{25})$			Threshold: 50th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1] < p_{50})$			Threshold: 75th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1] < p_{75})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Exam Participation									
Post× Low-Propensity	0.232***	0.232***	0.234***	0.166***	0.166***	0.170***	0.133***	0.133***	0.136***
	(0.014)	(0.014)	(0.014)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Pre-waiver Mean	0.53	0.53	0.53	0.68	0.68	0.68	0.76	0.76	0.76
adj. R^2	0.24	0.25	0.25	0.23	0.23	0.24	0.22	0.22	0.23
B. Exam Pass									
Post× Low-Propensity	0.061***	0.062***	0.076***	0.044***	0.045***	0.059***	0.029***	0.031***	0.043***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.008)	(0.008)
Pre-waiver Mean	0.28	0.28	0.28	0.34	0.34	0.34	0.41	0.41	0.41
adj. R^2	0.17	0.18	0.28	0.18	0.19	0.28	0.17	0.19	0.27
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Subject FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓		✓	✓
8th Grade z-scores			✓			✓			✓
Observations	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514
Number of Students	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419

Notes.- Observations are at the course level. The sample includes all second semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. The coefficients are estimated using Linear Probability model with standard errors clustered at the school level. In columns 1-3 (4-6), courses are categorized into Low and High propensity groups using 25th (75th) percentile threshold of predicted probability distribution in the pre-waiver data.
* p<0.10; ** p<0.05; *** p<0.01

Figure 8: Algorithm-driven DD Estimates at Different Propensity Thresholds



Notes.- The sample includes all second semester or year-long AP courses between SY 2010-11 and 2016-17, except AP Research and Capstone courses. The coefficients are estimated using Linear Probability model with standard errors clustered at the school level. Courses are categorized into Low and High propensity groups using 10th to 90th percentile thresholds with 5 points increment from the predicted probability distribution of the pre-waiver data. The low-propensity group consists of courses below the percentile threshold specified in x-axis, and the control group is consisted of courses with predicted probabilities equal or greater than the specified threshold.

ONLINE APPENDIX

A Model Selection

To predict AP exam-taking probabilities in absence of the fee waivers, we train and cross-validate three classification models—logistic regression (logit), Random Forest (RF), and Extreme Gradient Boosting (XGBoost)—on 282,554 observations from the pre-waiver period (AY 2010-11 to 2013-14). We used a 2-fold or 50% random sample cross-validation.

The binary indicator for AP exam participation for a given AP course is our outcome variable. Our model features included 183 variables including student demographic and academic variables: gender, race, low-SES, high school grade, and 8th grade Math and Reading scores; and binary indicators for course subjects and school districts.

Model Intuition.– Logistic regression models the probability of a binary outcome using a linear combination of predictors transformed by the logistic function. The model assumes a linear relationship between the covariates and the log-odds of the outcome and often fails to capture nonlinearities and interactions if explicitly not modeled. Classification trees can overcome this limitation and are found to perform well in real-world data (Caruana & Niculescu-Mizil, 2006). For model selection, we compare the performance of the logit model to Random forests and XGboost models. The Random forest models are built on decision trees, which classify student-courses as ”taking” (1) or ”not taking” (0) the exam by repeatedly splitting the sample at different thresholds of each explanatory variable until a set of decision rules have been developed to sort unseen data into each category (Breiman, 2001). We test the random forest model because it is better able to learn nonlinearities in the relationship between test taking and explanatory variables while maintaining some interpretability via decision tree diagrams. Whereas random forests makes predictions by combining the predictions of many individual decision trees, XGBoost creates decision trees sequentially and trains each new tree to correct the errors of the prior one (Chen & Guestrin, 2016).

Model Selection.– Our objective is to select the most accurate (but not unfair) model for predicting the probability that a student will take the AP exam for a given course. For this, we use the Area Under the Receiver Operating Characteristic curve (AUC-ROC) as our primary performance metric. AUC-ROC is the ideal measure because it evaluates a model's fundamental ability to distinguish between courses that lead to an exam and those that do not, independent of any single classification threshold.

Table A.1: Model Performance Metrics

Model	AUC-ROC	Misclassifications Error
Logistic Regression	0.842	0.156
Random Forest	0.846	0.054
eXtreme Gradient Boosting	0.864	0.165

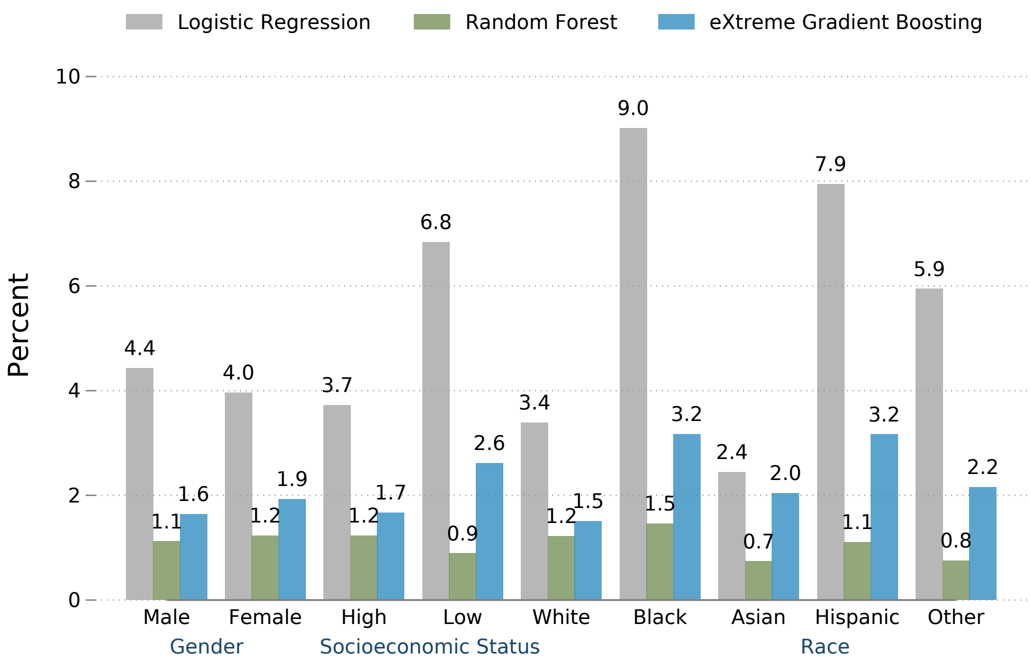
Table A.1 reports the model performance metrics. The eXtreme Gradient Boosting (XGBoost) model achieved the highest AUC-ROC score (0.864), indicating it is the best model for distinguishing between enrollments that will and will not culminate in the AP exam. To put things into perspective, an AUC-ROC of 0.864 implies that if you randomly pick one course where the student took the exam and another where the student did not, there is an 86.4% chance the model correctly assigns a higher probability to the first case. This demonstrates the model has excellent discriminative power and is effective at separating low- and high- propensity courses across all possible thresholds. Although the Random Forest model had a lower misclassifications error (0.054), this metric is only valid at 0.50 propensity threshold. Therefore, based on the threshold-independent performance measured by AUC-ROC, we select XGBoost as the most robust and reliable model for our setting.[21]

Algorithm Fairness.– To ensure that our chosen predictive model is equitable, we compare the False Negative Rates (FNR) each model produced across various demographic groups (Pleiss et al., 2017; Rambachan et al., 2020). Figure A.1 shows that logit model predictions result in largely different false negative rates across various demographic groups, especially across race and socioeconomic status categories—classifying a higher proportion of actual exams taken as untaken for Black, Hispanic, and low-SES students compared to their demographic counterparts. In contrast, the false negative rates across demographic groups show relatively less variability for XGBoost and random

[21] Our best-performing XGBoost model is specified with learning rate=0.01, maximum depth=5, and 150 boosting trees.

forest predictions.

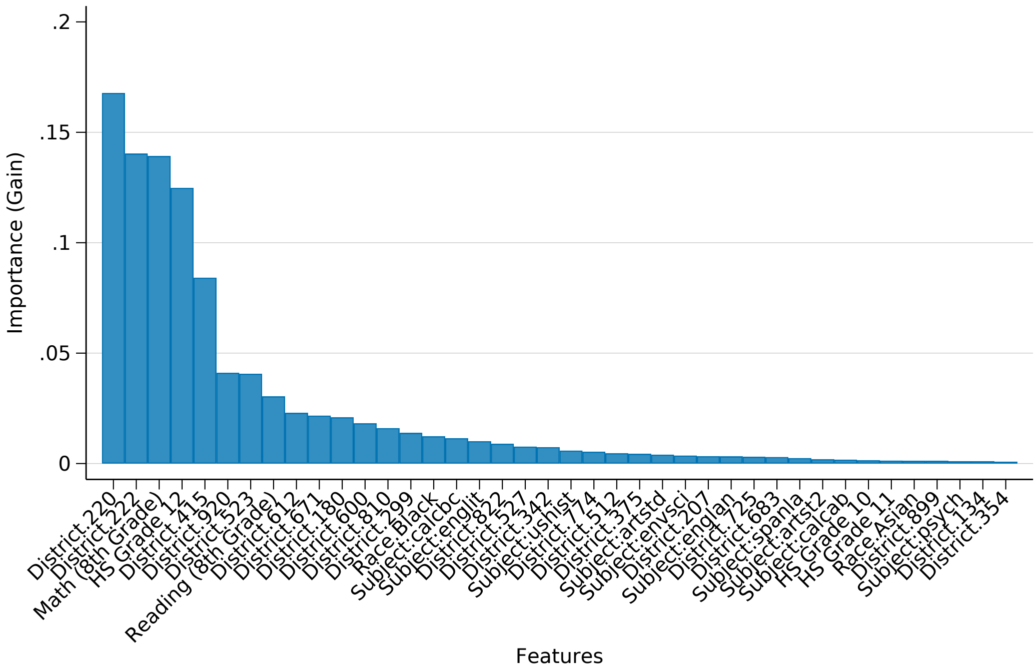
Figure A.1: False Negative Rates by Demographic Groups



Variable Importance.– Our selected XGBoost model gives importance to 67 variables, the top 40 of which are reported in Figure A.2. It highlights that school district binary indicators are the most prevalent and important predictors of AP exam participation in the pre-waiver period, as the trees grown by splitting on these variables substantially reduce prediction error (y-axis).[22] This could be due to local subsidy policies, test-center availability, or other unobservable factors, which our model captures.

[22]The district codes are randomly generated 3-digit numbers.

Figure A.2: XGBoost Feature Importance



Notes.- Randomly generated 3-digit numbers are used to replace the true district or Local Education Agency (LEA) codes.

B Benefit-Cost Analysis

We use the unified welfare analysis framework of Hendren and Sprung-Keyser (2020) to calculate Marginal Value of Public Funds (MVPF), which estimates the net benefits per $1 spent on fee waivers. In our application, the MVPF is calculated by dividing the an AP enrollee's willingness to pay (WTP) for an AP exam by its net cost to the state. We assume that an AP enrollees's maximum willingness to pay for a fee waiver equals the gain in the present value of their lifetime earnings from taking the exam.

We assume a causal chain where fee waivers increase AP exam participation, which in turn increases the likelihood of passing the exam, completing college, and ultimately, potential lifetime earnings. It follows that, by multiplying our estimated effect on pass rate by estimates of exam passing on on-time college completion (from Smith et al. (2017)), we can calculate the fee waivers' effect on college completion.[23] This we then multiply with the net present value of the college wage premium (from Bartik et al. (2016)) for general and low-SES students separately, approximating their respective WTP.[24]

We compare the student's benefit to the government's net cost of waiving AP exam fees. The government faces a constant marginal cost per AP exam, which differs for low-income students after a standard College Board fee reduction.[25] The government receives the net present value of future revenue from taxes paid on income generated by the fee waiver policy, which is taxed at a flat 3.99% rate as of 2026 (North Carolina Department of Revenue, 2025). The net cost of an additional fee waiver is the per-exam cost minus the tax revenue generated by the exam.[26] We then compute the MVPF as follows:

[23] We acknowledge that college completion effect of passing AP exams vary substantially by AP subjects. Notably, ∼46% of our low-propensity courses (defined from a Median split) are composed of underutilized courses, increasing on-time college completion probability by an average 0.5 percentage points [calculated from the Table A3 of (Smith et al., 2017)]. We, therefore, adjust the effect of passing a low-propensity course on college completion in Row 2 of Table B.1.

[24] Bartik et al. (2016) report the net present value of additional lifetime earnings associated with college completion in 2012 dollars, discounted at a 3% rate based on earnings from ages 25-79. The estimates are different for low-SES students ($314,800) and for the general student population ($846,300.50). See Table 3 in Bartik et al. (2016) for additional details.

[25] To align our cost data with the 2012 benefit estimates from Bartik et al. (2016), we use the 2012 AP exam cost of $87. For low-income students, we calculate a comparable 2012 cost by applying the 2025 subsidized-to-full-cost ratio ($53/$99). This yields a cost of $46.58 for low-income students, which is 53.5% of the full 2012 price. While direct out-of-pocket costs for low-income students were lower in 2012, we use the current subsidy structure as it reflects the federal subsidy policy from which the College Board's discount is derived, making our analysis more relevant to the current policy landscape.

[26] Our benefit-cost analysis builds on the framework of Bartik et al. (2016) with three additional

$$MVPF = \frac{\text{PV}(\Delta \text{ After-Tax Earnings})}{\text{Cost of Exam Fee} - \text{PV}(\Delta \text{ Tax Revenue})}$$

Results from the equation above can be interpreted as the benefit to individuals and the government associated with $1 of additional spending on fee waivers. For example, an MVPF of 2 implies that every dollar of government spending generates $2 worth of benefits.[27]

Table B.1: The Marginal Value of Public Funds for AP Fee Waivers

Group Receiving Waiver	**Effect on Pass Rate**	**Effect of Passing on College Completion**	**Benefit to Student**	**Net Cost to State**	**MVPF**
Low-SES Students	0.030	0.010	$90.67	$42.96	2.11
Students with Low Exam-Taking Propensity	0.059	0.008	$353.17	$65.68	5.28

Notes.- The effect of passing an AP exam linked to a given course on on-time (4-year) college completion come from (Smith et al., 2017). We use a more conservative version of their estimates in Row 2 to reflect that many students in courses we identify as low-propensity to take the exam are enrolled in AP classes that are not found to increase the odds of college graduation by Smith et al. (2017).

We analyze the returns to fee waivers at the student-course (or enrollment) level in Table B.1. We find that every dollar spent on a waiver for a low-SES student enrollment yields $2.11 in benefits. Waivers targeted toward enrollments with a low predicted propensity for exam participation yield benefits of $5.28.[28] However, perfectly targeting these high-return enrollments is difficult, as they are not explicitly identified in administrative data. Since these low-propensity enrollments comprise half of our sample (representing the below-median pre-waiver distribution), a universal policy by definition reaches a high-return target approximately 50% of the time. Even after adjusting costs to reflect that the state must fund roughly two waivers to reach one low-propensity enrollment, a

assumptions: (i) AP credit does not reduce public higher-education subsidies; (ii) AP credit generates no direct tuition or time savings for students once in college, and (iii) the per-student administrative costs of the program are zero. The first two assumptions likely attenuate our MVPF estimates, while the third creates a potential upward bias.

[27]We note that our estimates for low-SES enrollments and low-propensity enrollments come from different samples: the former uses results from our student fixed effects approach, while the latter uses the full sample of AP-enrolled students from our algorithm-driven approach. As such, direct comparability of these estimates relies on the assumption that the estimated effect for low-SES students in the multiple AP course taker sample generalizes to the full population of low-SES students.

[28]In our analysis, low-propensity enrollees are student-courses with below-median predicted exam-taking probabilities. These are a mix of high- and low-SES students, creating uncertainty around the costs and benefits of issuing a waiver since both wage premia and per-exam costs differ across these groups. To address this, we weight the estimated exam cost and wage increases by the expected share of low- and high-SES students in the low-propensity group to arrive at expected cost and benefit figures.

universal policy still delivers strong implied returns of ≈\$2.64 per \$1 spent.

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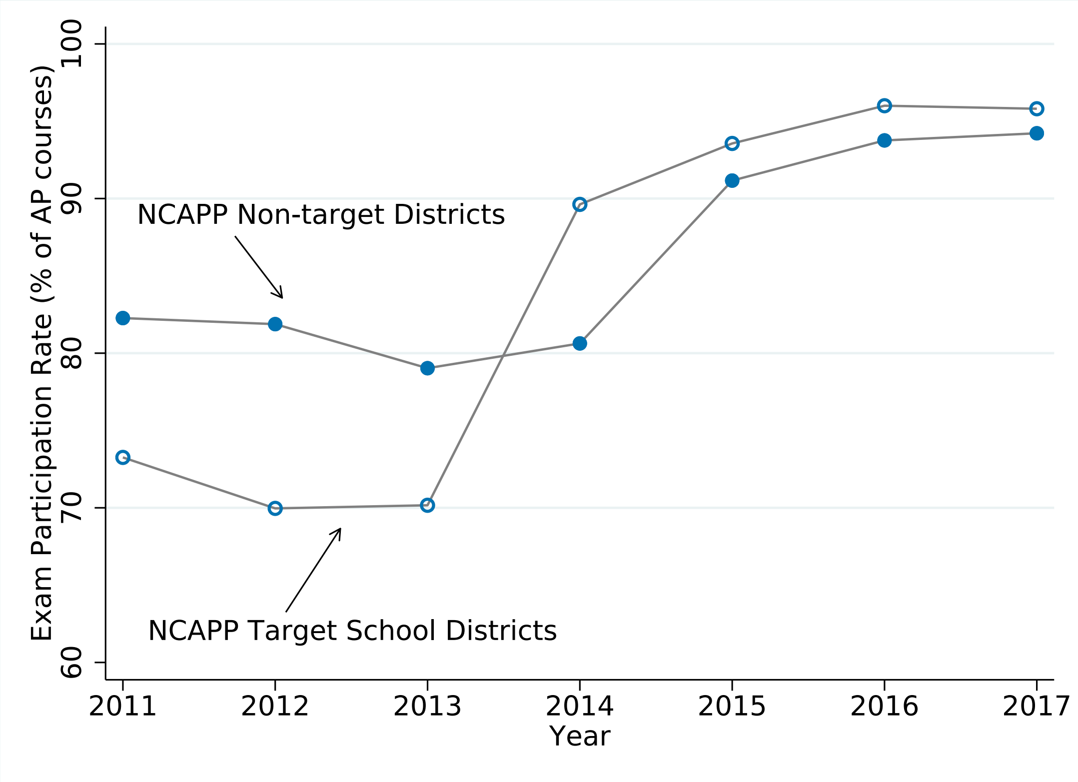
C Supplementary Tables and Figures

Figure C.1: Trends in AP Exam Participation by NCAPP Target



Notes.- This figure plots the trend in exam participation rates (as percent of AP courses) among 23 NCAPP target school districts versus the other school districts.

Table C.1: Individual Fixed Effects Estimates
(with Additional Time-varying Controls)

	(1) Full Model	(2) +National Pass Rate among AP Exam Takers by Subject	(3) +4-year High School Graduation Rate
A. Exam Participation			
Post	0.021***	0.019***	0.019***
	(0.004)	(0.004)	(0.004)
Pre-waiver Mean	0.90	0.90	0.90
adj. R^2	0.45	0.45	0.45
B. Exam Pass			
Post	0.002	0.003	0.002
	(0.006)	(0.006)	(0.006)
Pre-waiver Mean	0.57	0.57	0.57
adj. R^2	0.42	0.44	0.52
Observations	91,810	91,810	91,810
Number of Students	20,159	20,159	20,159

Notes.- All specifications include individual, high school grade, AP subject, and teacher fixed effects. Observations are at the course level. The sample includes high school students who have taken AP courses both before and after the implementation of the AP exam fee waivers in SY 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test. The coefficients are estimated using Linear Probability model with standard errors clustered at the individual level.
* p<0.10; ** p<0.05; *** p<0.01

Table C.2: Individual Fixed Effects Estimates
(Study Period: 2012-2015)

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. Exam Participation			
Post	0.046***	0.046***	0.032***
	(0.005)	(0.005)	(0.006)
Pre-waiver Mean	0.90	0.90	0.90
adj. R^2	0.33	0.34	0.46
B. Exam Pass			
Post	-0.015*	0.003	0.006
	(0.008)	(0.008)	(0.009)
Pre-waiver Mean	0.58	0.58	0.58
adj. R^2	0.42	0.44	0.52
Observations	76,132	76,132	76,132
Number of Students	19,305	19,305	19,305

Notes.- All specifications include individual and high school grade fixed effects. Observations are at the course level. The sample includes high school students who have taken AP courses both before and in the first year of implementation of the AP exam fee waivers in SY 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test. The coefficients are estimated using Linear Probability model with standard errors clustered at the individual level.
* $p<0.10$; ** $p<0.05$; *** $p<0.01$

Table C.3: Heterogeneous Effects
(Study Period: 2012-2015)

(a) Outcome: Exam Participation

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.029***	0.024***	0.026***
	(0.005)	(0.005)	(0.006)
Pre-waiver Mean (Underutilized)	0.90	0.90	0.90
adj. R^2	0.33	0.34	0.46
B. By Student Socioeconomic Status			
Post×Low-SES	0.033***	0.033***	0.027***
	(0.008)	(0.008)	(0.007)
Pre-waiver Mean (Low-SES)	0.87	0.87	0.87
adj. R^2	0.33	0.34	0.46
C. By Student Race/Ethnicity			
Post×URM	0.042***	0.042***	0.034***
	(0.007)	(0.007)	(0.006)
Pre-waiver Mean (URM)	0.84	0.84	0.84
adj. R^2	0.33	0.34	0.46
Observations	76,132	76,132	76,132
Number of Students	19,305	19,305	19,305

Notes.- See Table C.2 notes.* p<0.10; ** p<0.05; *** p<0.01

(b) Outcome: Exam Pass

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.042***	0.028***	0.018*
	(0.008)	(0.008)	(0.010)
Pre-waiver Mean (Underutilized)	0.62	0.62	0.62
adj. R^2	0.42	0.44	0.52
B. By Student Socioeconomic Status			
Post×Low-SES	0.038***	0.032***	0.036***
	(0.009)	(0.009)	(0.010)
Pre-waiver Mean (Low-SES)	0.36	0.36	0.36
adj. R^2	0.42	0.44	0.52
C. By Student Race/Ethnicity			
Post×URM	0.018**	0.014*	0.008
	(0.008)	(0.008)	(0.008)
Pre-waiver Mean (URM)	0.40	0.40	0.40
adj. R^2	0.42	0.44	0.52
Observations	76,132	76,132	76,132
Number of Students	19,305	19,305	19,305

Table C.4: Individual Fixed Effects Estimates
(Includes NCAPP Target Districts)

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. Exam Participation			
Post	0.035***	0.036***	0.020***
	(0.003)	(0.003)	(0.004)
Pre-waiver Mean	0.90	0.90	0.90
adj. R^2	0.33	0.33	0.45
B. Exam Pass			
Post	-0.001	0.007	0.001
	(0.005)	(0.005)	(0.006)
Pre-waiver Mean	0.57	0.57	0.57
adj. R^2	0.41	0.44	0.51
Observations	96,359	96,359	96,359
Number of Students	20,955	20,955	20,955

Notes.- All specifications include individual and high school grade fixed effects. Observations are at the course level. The sample includes high school students, including students from NCAPP target school districts, who have taken AP courses both before and after the implementation of the AP exam fee waivers in SY 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test. The coefficients are estimated using Linear Probability model with standard errors clustered at the individual level.
* p<0.10; ** p<0.05; *** p<0.01

Table C.5: Heterogeneous Effects
(Includes NCAPP Target Districts)

(a) Outcome: Exam Participation

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.033***	0.018***	0.019***
	(0.006)	(0.006)	(0.007)
Pre-waiver Mean (Underutilized)	0.88	0.88	0.88
adj. R^2	0.33	0.33	0.45
B. By Student Socioeconomic Status			
Post×Low-SES	0.044***	0.044***	0.025***
	(0.007)	(0.007)	(0.007)
Pre-waiver Mean (Low-SES)	0.86	0.86	0.86
adj. R^2	0.33	0.33	0.45
C. By Student Race/Ethnicity			
Post×URM	0.059***	0.059***	0.037***
	(0.006)	(0.006)	(0.006)
Pre-waiver Mean (URM)	0.83	0.83	0.83
adj. R^2	0.33	0.33	0.45
Observations	96,359	96,359	96,359
Number of Students	20,955	20,955	20,955

Notes.- See Table C.4 notes. * p<0.10; ** p<0.05; *** p<0.01

(b) Outcome: Exam Pass

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post×Underutilized	0.066***	0.017*	-0.011
	(0.009)	(0.009)	(0.011)
Pre-waiver Mean (Underutilized)	0.60	0.60	0.60
adj. R^2	0.41	0.44	0.51
B. By Student Socioeconomic Status			
Post×Low-SES	0.033***	0.026***	0.029***
	(0.009)	(0.009)	(0.009)
Pre-waiver Mean (Low-SES)	0.36	0.36	0.36
adj. R^2	0.41	0.44	0.51
C. By Student Race/Ethnicity			
Post×URM	0.016**	0.011	0.009
	(0.007)	(0.007)	(0.007)
Pre-waiver Mean (URM)	0.39	0.39	0.39
adj. R^2	0.41	0.44	0.51
Observations	96,359	96,359	96,359
Number of Students	20,955	20,955	20,955

Table C.6: Heterogeneous Effects
(Alternative Specification)

(a) Outcome: Exam Participation

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post	0.032***	0.033***	0.017***
	(0.004)	(0.004)	(0.004)
Post×Underutilized	0.026***	0.020***	0.022***
	(0.004)	(0.005)	(0.006)
Pre-Mean (Underutilized)	0.90	0.90	0.90
adj. R^2	0.34	0.34	0.45
B. By Student Socioeconomic Status			
Post	0.032***	0.032***	0.018***
	(0.004)	(0.004)	(0.004)
Post×Low-SES	0.035***	0.035***	0.026***
	(0.007)	(0.007)	(0.007)
Pre-waiver Mean (Low-SES)	0.86	0.86	0.86
adj. R^2	0.34	0.34	0.45
C. By Student Race/Ethnicity			
Post	0.028***	0.028***	0.015***
	(0.004)	(0.004)	(0.004)
Post×URM	0.046***	0.046***	0.035***
	(0.006)	(0.006)	(0.006)
Pre-waiver Mean (URM)	0.84	0.84	0.84
adj. R^2	0.34	0.34	0.45
Observations	91,810	91,810	91,810
Number of Students	20,159	20,159	20,159

Notes.- See Table 3 notes. * p<0.10; ** p<0.05; *** p<0.01

(b) Outcome: Exam Pass

	(1) Baseline	(2) +Subject FE	(3) +Teacher FE
A. By Course Type			
Post	-0.006	0.003	-0.001
	(0.006)	(0.005)	(0.006)
Post×Underutilized	0.041***	0.022***	0.013
	(0.007)	(0.008)	(0.009)
Pre-waiver Mean (Underutilized)	0.62	0.62	0.62
adj. R^2	0.41	0.44	0.51
B. By Student Socioeconomic Status			
Post	-0.006	0.003	-0.002
	(0.006)	(0.006)	(0.006)
Post×Low-SES	0.037***	0.029***	0.032***
	(0.009)	(0.009)	(0.009)
Pre-waiver Mean (Low-SES)	0.36	0.36	0.36
adj. R^2	0.41	0.44	0.51
C. By Student Race/Ethnicity			
Post	-0.005	0.004	0.000
	(0.006)	(0.006)	(0.006)
Post×URM	0.016**	0.013*	0.011
	(0.007)	(0.007)	(0.008)
Pre-waiver Mean (URM)	0.40	0.40	0.40
adj. R^2	0.41	0.44	0.51
Observations	93,171	93,171	93,171
Number of Students	20,641	20,641	20,641

Table C.7: Individual Fixed Effects Estimates
(All within-student observations, No Teacher Fixed Effects)

	(1) Baseline	(2) +Subject FE
A. *Outcome:* Exam Participation		
Post	0.038***	0.038***
	(0.003)	(0.003)
Pre-Mean	0.90	0.90
adj. R^2	0.36	0.37
B. *Outcome:* Exam Pass		
Post	0.001	0.006
	(0.005)	(0.005)
Pre-Mean	0.57	0.57
adj. R^2	0.41	0.44
Observations	103,786	103,786
Number of Students	22,075	22,075

Notes.- All specifications include individual and high school grade fixed effects. Observations are at the course level. The sample includes high school students who have taken AP courses both before and after the implementation of the AP exam fee waivers in Y 2014-15. The AP enrollees are identified as taking the second-semester or year-long courses linked to a given AP test. The coefficients are estimated using Linear Probability model with standard errors clustered at the individual level. * p<0.10; ** p<0.05; *** p<0.01

Table C.8: Algorithm-driven Difference-in-Differences Estimates
Predictive Model: Logit

	Threshold: 25th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{25})$			Threshold: 50th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{50})$			Threshold: 75th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{75})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Exam Participation									
Post× Low-Propensity	0.260***	0.260***	0.263***	0.194***	0.194***	0.196***	0.147***	0.148***	0.148***
	(0.014)	(0.014)	(0.014)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Pre-waiver Mean	0.50	0.50	0.50	0.66	0.66	0.66	0.75	0.75	0.75
adj. R^2	0.25	0.25	0.26	0.23	0.24	0.25	0.22	0.23	0.24
B. Exam Pass									
Post× Low-Propensity	0.071***	0.073***	0.088***	0.061***	0.062***	0.073***	0.057***	0.058***	0.062***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.010)	(0.009)	(0.008)
Pre-waiver Mean	0.27	0.27	0.27	0.38	0.38	0.38	0.43	0.43	0.43
adj. R^2	0.16	0.18	0.28	0.16	0.17	0.28	0.16	0.17	0.27
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Subject FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓		✓	✓
8th Grade z-scores			✓			✓			✓
Observations	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514
Number of Students	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419

Notes.- See Table 6 notes. * p<0.10; ** p<0.05; *** p<0.01

Table C.9: Algorithm-driven Difference-in-Differences Estimates
Predictive Model: Random Forest

	Threshold: 25th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{25})$			Threshold: 50th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{50})$			Threshold: 75th Percentile Low-Propensity=$\mathbf{I}(Pr[Take=1]<p_{75})$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Exam Participation									
Post× Low-Propensity	0.601***	0.601***	0.603***	0.285***	0.285***	0.287***	0.178***	0.179***	0.183***
	(0.013)	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Pre-waiver Mean	0.26	0.26	0.26	0.62	0.62	0.62	0.75	0.75	0.75
adj. R^2	0.52	0.52	0.52	0.28	0.28	0.29	0.23	0.23	0.24
B. Exam Pass									
Post× Low-Propensity	0.260***	0.265***	0.285***	0.119***	0.122***	0.135***	0.055***	0.058***	0.083***
	(0.011)	(0.011)	(0.011)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
Pre-waiver Mean	0.21	0.22	0.31	0.17	0.19	0.28	0.16	0.17	0.28
adj. R^2	0.14	0.14	0.14	0.34	0.34	0.34	0.43	0.43	0.43
Grade FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Subject FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
School FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓		✓	✓		✓	✓
8th Grade z-scores			✓			✓			✓
Observations	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514	556,514
Number of Students	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419	214,419

Notes.- See Table 6 notes. * p<0.10; ** p<0.05; *** p<0.01