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Abstract

Taking advanced courses in high school is associated with many positive high school and college outcomes. States and school districts are increasingly interested in more systematic approaches to identify qualified students for advanced course work. We developed an automatic notification tool, which used universal screening and a behavioral nudge for Grade 9 students to increase advanced course participation. The tool was embedded in the Course Planner of a student information system used in thousands of schools across the U.S. We conducted a large-scale cluster randomized controlled trial of the tool, randomizing 110 high schools in 44 districts to one of three conditions: a short-form notification, a long-form notification, or no notification. The tool did not significantly increase Grade 10 course outcomes, but both treatments had large, significant effects on Grade 11 course planning, with students in both treatments 22-24 percentage points more likely to plan any advanced course, 8-13 percentage points more likely to plan an advanced English language arts course, and 23-24 percentage points more likely to plan an advanced math course than students in the control condition.

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Introduction

Taking advanced courses in high school is associated with college and career readiness, college enrollment, and college completion (An, 2013; Long et al., 2012). The benefits of advanced courses are especially large for students from low-income backgrounds and students who are Black and Hispanic (Austin et al., 2024; Card & Giuliano, 2014, 2016), but after accounting for prior achievement, these students are less likely to enroll in the advanced courses their school offers than their peers (e.g., Austin, 2017; Darity et al., 2001; Xu et al., 2021). As a result, each year hundreds of thousands of eligible high school students miss out on the opportunity to take advanced courses (Theokas & Saaris, 2013; Xu et al., 2021).

To increase accelerated or advanced course taking opportunities for all qualified students, states and school districts are increasingly interested in using universal screening to identify and place students into advanced courses. Automatic enrollment policies have proliferated in recent years: since 2018, at least eight states and several districts have passed policies, and legislation has been proposed in several other states as well as nationally (Advanced Coursework Equity Act, 2023; EdTrust, 2024; Plucker, Berg, & Kuwayama, 2024). The policies set a threshold based on objective performance measures—often standardized test scores—and require districts to screen all students against the threshold and automatically enroll students who meet or exceed the threshold in a subject area into a more advanced course in that subject (such as honors rather than regular geometry, or Advanced Placement [AP] rather than regular English). Parents are notified and given the opportunity to opt their child out if they choose. Most policies apply to all course subjects and cover students in high school, with some extending to middle and elementary school and a couple focusing exclusively on middle school (EdTrust, 2024; Plucker et al., 2024).

Rigorous evidence about the effectiveness of automatic enrollment policies comes from the Wake County Public School System (PSS) in North Carolina, and Dallas Independent School District (ISD) in Texas, which focused on accelerating students in middle school math, and from Washington state, which focused on accelerating students in Grades 11 and 12 in math, English, and Social Studies. These studies found that automatic enrollment policies did in fact increase participation in advanced courses among students who otherwise were likely to be overlooked using traditional identification methods like teacher or school counselor recommendations. Difference-in-differences (DiD) results from Dallas ISD found their policy increased participation in Algebra 1 by Grade 8 (Casteño et al., 2025). Regression discontinuity results from Wake County PSS found their policy increased completion of Algebra 1 by Grade 8, although most of the effects faded out by the time students reached precalculus in high school (Dougherty et al., 2015, 2017). DiD results from Washington state found the policy increased participation in advanced courses in Grades 11 and 12 (Austin et al., 2025).

While research shows these policies increase advanced course participation, it can take years to develop and pass legislation and implement new policies, which presents a barrier to scalability. Consequently, we developed an alternative, rapidly scalable approach: an automatic notification tool embedded in a Student Information System (SIS). Like automatic enrollment policies, the tool uses universal screening to identify students for advanced course participation. Instead of enrolling students directly, the tool takes a softer-touch approach to allow flexibility across large numbers of districts and states. When students who meet or exceed the performance threshold log into their Course Planner within the SIS, the tool notifies them that they could succeed in an advanced course and recommends advanced courses to consider. Similarly, when students' parents and school counselors log into the Course Planner, the tool notifies them of the student's readiness for advanced coursework. Embedding the automatic notification process into the SIS facilitates scalability because the tool operates within schools' existing course selection processes and the SIS software serves 8 million students per year in hundreds of districts across nearly 40 states.

This article presents findings from a large-scale, three-arm cluster randomized-controlled trial (RCT) conducted with 110 U.S. high schools across 44 districts examining the effects of the notification tool compared with no notification on students' interest, enrollment, and success in advanced courses.[1] We report findings for two main research questions (RQs):

1. What is the effect of an automatic notification tool on students' selection of, enrollment, and success in advanced Grade 10 courses and their selection of advanced Grade 11 courses?
2. Does the effect of the tool vary by whether students received the basic short-form (T1) or expanded long-form (T2) notification text?

In addition to the confirmatory results, we report findings for three exploratory RQs. The first two are based on supplemental analyses of the quantitative data, and the third draws

[1] The study and analysis plan were pre-registered at the Registry of Efficacy and Effectiveness Studies (REES) after the study started but prior to the analysis of outcomes (Registry ID #17880.1). The study research activities were approved by the American Institutes for Research Institutional Review Board.

on a small sample of survey responses and interviews with counselors in treatment districts:

3. What school characteristics (racial/ethnic composition, number of Grade 9 and 10 students served), district characteristics (locale), and student characteristics (race/ethnicity, special education status [whether or not the student has an IEP], English Learner [EL] status, sex, prior grade in reading, and prior grade in math)[2] are associated with increased enrollment and success in advanced high school courses?[3]
4. What types of engagement with the tool are associated with increased planning of and enrollment in advanced high school courses?
5. How do school counselors use the automatic notification tool when making course assignments for their students or advising students on their course choices?

We found that the tool did not significantly increase Grade 10 course outcomes, but that both treatments had large, significant effects on Grade 11 course planning outcomes. Students in T1 were 22 percentage points more likely to plan any advanced course, 13 percentage points more likely to plan an advanced English Language Arts (ELA) course, and 24 percentage points more likely to plan an advanced math course for Grade 11 than students in the control condition. Effects were similar in magnitude for students in T2, and, with the exception of advanced ELA, were also statistically significant. We also found some meaningful differences in effects by students' race/ethnicity and significant positive effects for students who are ELs compared with students who are not ELs.

Automatic Notification Tool and Theory of Action

The automatic notification tool consists of two primary mechanisms: universal screening and an informational nudge. The theory of action for the notification tool is presented in Figure 1. Universal screening gives every student the same consideration for advanced course eligibility, addressing the limitations of traditional identification methods that overlook many qualified students. Importantly, universal screening supplements but does not replace other routes to advanced course taking: students not identified as eligible for a notification may still be recommended by school staff or self-select into advanced courses.

Nudge interventions leverage behavioral economics to encourage advantageous behaviors. Informational nudges, in particular, are meant to encourage individuals to make

[2] In our pre-registered analysis plan, we also intended to explore the extent to which students' scores on ELA and math assessments were associated with increased enrollment and success in advanced courses. However, we were unable to conduct these exploratory analyses due to limitations of the data we received.
[3] Student-level data were not available on family income, eligibility for free- or reduced-price lunch, or other indicators of students' socioeconomic status (SES), so we were unable to include SES in our study.

beneficial decisions (Damgaard & Nielsen, 2018). Embedding the nudge at the point of action (in the course planner, on the same page where students enter their course selections) maximizes the link between the receipt of information and the targeted behavior of selecting an advanced course. Selecting an advanced course should, in turn, lead to advanced course enrollment, subject to district and school constraints.

The automatic notification tool was developed in 2022–2023 and built into the SIS's online academic planner module, which students, parents, and school counselors use to plan students' high school courses for grades 9–12. The tool required a one-time, nominal development cost and was deployed to participating districts as part of the SIS's regular update process, with no special action needed by districts to activate it and no cost to districts for using it. The tool was then active in treatment schools during the 2023–24 school year for students in Grade 9, who received notifications as they were choosing their courses for Grade 10 (and, for some students, Grades 11 and 12). Most students completed the course selection process between February and May of 2024. In the 2024–25 school year, students were expected to take Grade 10 courses and plan Grade 11 courses.

For this study, we tested two versions of the automatic notification tool for students in Grade 9 planning their courses for Grade 10 (and, in some cases, Grades 11 and 12). Students who met or exceeded the universal screening threshold (whom we refer to as eligible students) in schools randomly assigned to either of the treatment conditions, T1 or T2, received an alert in their academic planner (Figure 2). Eligible students may have received an alert for ELA, math, or both subjects depending on which thresholds they met. If students clicked on the alert, a pop-up opened that displayed the assigned notification text.

In T1 schools, eligible students and their parents/guardians and school counselors received a simple notification informing them their prior academic performance indicates they could do well in advanced courses and encouraging them to consider an advanced course for the following year (Figure 3). The notification also encouraged them to talk to their parents/guardians, teachers, and counselors to learn more about course options and opportunities for support (Bird et al., 2021).[4] In T2 schools, eligible students received a slightly longer notification with an added sentence informing them that taking advanced

[4] Parents and school counselors have their own SIS accounts and can log in to the academic planner module to view their student's course selections and support the planning process. Parents and counselors of eligible students received the same course planning alert and notification text as the student, with small adjustments to account for their relationship to the student (e.g., [Student name]'s performance shows they have the ability…"; "talk to [Student name] about their options…").

courses in high school can help students get into college, do well in college, and be ready for a career (see Figure 3; Mabel, et al., 2023). In both treatments, for each eligible subject, the notification text listed up to two examples of relevant Grade 10 advanced courses offered at the student's high school. In control schools, students and their parents and school counselors interacted with the standard, business-as-usual (BAU) version of the academic planner interface and did not see an alert or the notification text.

Literature Review

Universal screening. Historically, the process for identifying students for acceleration has not been systematic, relying instead on teachers or school counselors to identify students using a combination of factors—such as prior performance, teacher and counselor observations, and perceptions of student readiness—that introduce subjectivity (Anderson, 2022; Chin et al., 2020; Gershenson & Papageorge, 2018; Grissom & Redding, 2016). In contrast, universal screening evaluates every student for acceleration against the same criteria, reducing barriers associated with non-academic factors that inform traditional identification methods. In multiple studies, including studies of automatic enrollment policies, universal screening has been found to increase participation in accelerated opportunities and address under-identification of eligible students using traditional methods (Austin et al., 2024; Card & Guiliano, 2015, 2024; Castaño et al., 2025; Dougherty et al., 2015, 2017; Grissom & Redding, 2016; McBee, 2016). Screening criteria differ somewhat, but most automatic enrollment policies use state standardized assessment scores, and many policies set a minimum score equivalent to "Meets Grade Level" or "Proficient" in grade level standards. A notable exception to the proficiency cutoff approach is Wake County PSS; their policy identifies students in Grades 6–8 for accelerated math whose predicted probabilities of passing the state's Algebra 1 end of course exam were 70 percent or higher based on a proprietary algorithm (Dougherty et al., 2015).

We followed the common approach among automatic enrollment policies and set the tool's screening threshold at a score of proficient or higher on state standardized assessments. To include schools that do not record standardized test scores in the SIS and broaden eligibility, we conducted a second universal screen of students' course grade in their most recent relevant class.[5] Students who did not have test score data or did not have a proficient

[5] Most automatic enrollment policies do not set a course grade threshold. We analyzed the relationship between standardized test scores and course grades and set a course grade threshold that aligned with the proficiency threshold for the students in our sample.

test score, but had a grade of B- or higher, were also identified as eligible for a notification.

Informational nudges. The alert and notification text serve as an informational nudge encouraging students to select an advanced course. Automatic enrollment policies use a behavioral or default-choice nudge: instead of having to opt into advanced courses, students are automatically placed into advanced courses and must take action to opt out if they do not want to take the course (Damgaard & Nielsen, 2018). Informational nudges are a softer-touch approach, encouraging advanced course taking while providing flexibility to accommodate varying course registration practices and constraints (such as course availability or capacity to offer extra sections) when scaling the intervention across hundreds of schools and districts.

Information barriers contribute to underenrollment in advanced courses in several ways. Many college-aspiring students are unaware of the importance of advanced courses for college readiness and admissions processes (Diamond & Lewis, 2022; Grissom et al., 2019). Students also may be unaware of the advanced courses available at their school, or may be aware but believe they are not the “right” type of student for advanced courses (Domina et al., 2017; Lewis & Diamond, 2025; Tyson, 2011). To our knowledge, only two rigorous studies have examined the effect of informational nudges on high school coursetaking. In Wisconsin, researchers tested the effects of mailing brochures about the importance of taking math and science courses in high school to parents of students in tenth and eleventh grade; they found that students whose parents received the brochures took one additional semester of math or science during the last two years of high school compared with students whose parents did not receive the brochures (Harackiewicz, et al. 2012). More recently, Mabel and colleagues (2023) conducted an RCT of the effects of a College Board initiative that sent personalized letters and emails to eligible students in tenth grade and their parents with up to two personalized AP course recommendations, information about the benefits of advanced courses, and encouragement to ask their school counselor for guidance. The informational nudge significantly increased the probability of AP Exam participation by 1.1 percentage points and the probability of scoring 3 or higher on AP Exams by 0.5 percentage points.

More broadly, there is mixed evidence of the effectiveness of informational nudges in education. Smaller-scale, local interventions have more consistently positive effects that often decrease or disappear at scale (Bergman, Denning, and Manoli, 2019; Bird et al., 2021; Gurantz et al. 2021). Many large-scale interventions rely on notifications sent by entities with which students do not have personal connections, leading students to be less responsive to them (Arteaga et al., 2021; Bird et al., 2021; Castleman et al., 2021), whereas small-scale studies often leverage local organizations or close connections between students and a trusted adult (e.g., Castleman & Page, 2015; Page, Castleman, & Meyer, 2020). Further, inviting students to connect with a trusted adult, such as an advisor, for support may be more effective than information only—because it both engages close connections and presents a concrete step to take (Arteaga et al., 2022; Bird et al., 2021; Cohodes et al., 2025; Mabel et al., 2023).

Notification Design.

We designed the notification tool to incorporate effective nudging practices and address limitations of at-scale nudges based on the evidence from prior studies. Because our notification tool is embedded into the SIS tool schools already use for course planning, the notification appears to come from students' schools. It also encourages students to seek guidance from trusted adults (parents/guardians, teachers, and counselors). Both features leverage close connections despite large-scale implementation (Arteaga et al., 2022; Bird et al., 2021; Cohodes et al., 2025). We also personalized course recommendations and delivered them to the same location where the target action (planning an advanced course) takes place (Mabel et al., 2023). Finally, we kept the text short and sought to avoid dense information that requires too great a cognitive load (Bird et al., 2021; Glazerman et al., 2020), but we also tested the relative effectiveness of a longer notification that incorporated additional information on the utility value of advanced courses in T2 (Mabel et al., 2023).

Research Design

Eligibility and Sample.

We worked with the SIS provider from May to August 2023 to recruit districts to participate in the RCT. A district was eligible to participate in the study if it met the following criteria:

- Is a traditional public school district.
- Actively used the academic planner in 2022–23, defined as having at least 70 percent of students with a course planned for the 2023–24 school year in the Course Planner as of Summer 2023.
- Had at least one school that meets the school-level inclusion criteria.

Schools were eligible for inclusion in the study if they met the following criteria:

- Is a traditional public school.
- Had at least 70 percent of students with a course planned for the 2023–24 school year in the academic planner as of summer 2023.
- Had at least 15 Grade 10 students in the school in 2022–23.
- Offered at least one advanced course in ELA or math with at least two students enrolled in 2022–23.
- Used the SIS to record standardized test scores or course grades for math and/or ELA

for at least 70 percent of students.

We received consent to participate in the study from 55 districts. Based on the district and school eligibility criteria, we identified 110 eligible high schools in 44 districts. Using the Census-defined U.S. geographic regions, sixteen districts were in the Midwest, one was in the Northeast, seventeen were in the South, and ten were in the West. Within eligible schools, students were screened for eligibility to receive an automatic notification if they met the following criteria in Fall 2023:

- Were enrolled in Grade 9.
- Had a Grade 8 or 7 standardized test score or Grade 8 course grade in math or ELA.
- Were in a general education setting more than 80 percent of the school day.
- Were between ages 12 and 16 at any point during Grade 9.

The tool screened all Grade 9 students in the study sample using a two-step approach to determine eligibility to receive a notification. First, students who scored proficient or higher on their Grade 8 state standardized math test were identified as eligible for a math notification and, similarly, students who scored proficient or higher on their Grade 8 state standardized ELA test were eligible for an ELA notification.[6] Students who (a) did not have a standardized test score record in the SIS (usually because their schools did not use the SIS to manage test score records), or (b) scored below proficient on their Grade 8 standardized test were screened a second time using their Grade 8 course grades (see Table A1 for a breakdown of students identified as eligible based on each screen). Students in this category who earned a Grade 8 course grade of B- or higher were identified as eligible for a notification. Students missing both standardized test score data and course grade data were identified as ineligible.

Of the 37,861 students screened, 24,857 students were identified as eligible to receive a notification in ELA, math, or both subjects. These students comprise the overall sample of students at randomization. Analytic sample sizes vary somewhat by outcome due to missing data; the analysis-specific sample sizes are stated in the results tables.

Random Assignment and Baseline Equivalence. To conduct randomization for our cluster RCT, we randomly assigned the 110 eligible schools to one of three conditions, with equal probability of assignment to each condition. We stratified by district urbanicity (urban, suburban, town, and rural) and used constrained randomization (rerandomization) to ensure

[6] In a limited number of cases, Grade 7 standardized assessment scores were used to screen students who did not have standardized assessment or course grade data for Grade 8.

balance on key covariates (Morgan & Rubin, 2015; Wang et al., 2023; What Works Clearinghouse [WWC], 2022). At the school level, we prioritized balance on overall advanced course participation, operationalized as the percent of Grade 10 students who took at least one advanced course in 2022-23, and demographic representation in advanced courses, operationalized as the percent of Grade 10 students in advanced courses who were from a racial/ethnic group often underrepresented in advanced courses (students who are Black or Hispanic) and who were White. At the student level, we prioritized balance on eligibility criteria: the percentage of Grade 9 students in 2023-24 who were eligible for an ELA notification, the percentage who were eligible for a math notification, and the average prior ELA and math grades. We also examined balance on a second tier of variables. See Table 1 for descriptive statistics and baseline equivalence across treatment conditions.

In an RCT, spillover, or unintentional, effects can occur if participants in one condition are exposed to the intervention intended for participants in another condition. In this study, spillover effects could occur if students assigned to one of the treatment conditions or their school counselors discuss the notification they received with students or counselors assigned to another condition. We mitigated against this by randomizing at the school level, so that all eligible students in a school experience the same treatment condition and school counselors experience the same condition for all their eligible students.

Among the 110 randomized schools, 66 percent and 59 percent of students in T1 were identified as eligible based on ELA and math performance, respectively; as were 67 percent and 60 percent of students in T2, and 58 percent and 53 percent of students in the control condition.[7] This resulted in a sample of 24,857 eligible students at the time of randomization; 7,831 were in the 36 schools assigned to T1, 8,166 were in the 37 schools assigned to T2, and 8,860 were in the 37 schools assigned to the control condition. We provided a list of schools in each condition to the SIS, and they ensured that the correct version of the tool was active for schools in each treatment condition and inactive for schools in the control condition.

Data

The primary data sources for this study are student-level administrative data and student-level software usage data from the SIS provider. The data included information on student demographic characteristics (race/ethnicity, sex, special education status, and EL status)' school enrollments; standardized test scores; high school courses planned, scheduled,

[7] Schools in the control condition were larger, on average, than schools in the treatment conditions; this contributed to larger numbers of eligible students but smaller proportions of eligible students in control schools.

rostered, attempted, and completed; and course grades. We used these data to construct school-level demographic variables and merged in district-level NCES locale codes.

Data Used to Program the Tool and Define the Sample. To identify students eligible for a notification, the research team used standardized test score data and course grade data from the 2022–23 school year.[8] To identify advanced courses for recommendation, the research team used data on Grade 10 course offerings from the 2022–23 school year. We took several steps to clean and standardize the course data for analysis. We first cleaned course names to standardize as much as possible across schools and districts. We then used pattern-matching with regular expressions within the cleaned course names to label course subjects as either math or ELA and flag advanced courses in each subject. The team reviewed the course lists and manually refined the patterns to minimize misclassification. Once advanced courses were identified and labeled, we ranked them within each school by student enrollment size.

The tool dynamically generated the recommended courses that appeared in the notification text from the list of advanced courses in each school identified by the research team. The dynamic process involved applying filters already in place in the Course Planner that prevent students from selecting courses for which they are ineligible, including courses for which students had not yet met all prerequisite requirements and courses students had already taken. Of the remaining courses, the tool prioritized recommending those that had the largest enrollment in the 2022–23 school year and therefore were likely to have the largest supply in the 2023–24 school year. The SIS logged the delivery and content of each recommendation to verify the correct treatment was delivered to students in each condition.

Notifications were pushed (or sent) to users at the time of login, allowing them to then click on the notification to read the recommendation text. Data on users' interaction with the notification tool was recorded in an "event log," which captured interactions at the user level, such that for each student, we can see separate interactions with that student's course planner for the student, their parent/guardian(s), and school staff members. Event log data included information on users' engagement with the Course Planner and notification, including number of logins to the Course Planner, number of times the course recommendation alert appeared for a user, number of views of the notification text (measured as (a) number of clicks on the course recommendation alert and (b) number of times the notification text was open for at least three seconds, corresponding with the average time needed to read the text),

[8] In the limited number of cases where Grade 7 standardized assessment data were used, these data came from 2021–22 administrative data.

and duration of each view of the notification text.

Data Used to Conduct Outcome Analyses. To identify students' planned and scheduled courses, we used event log data from the 2023–24 school for Grade 10 courses planned and scheduled and the 2024–25 school year for Grade 11 courses planned. We received data on Grade 10 courses planned and scheduled in July 2024 and data on Grade 11 courses planned in July 2025. The event log collected information about students' course selections during the course planning process, including courses chosen at each time a student's course plan was saved. This information was used to code two outcomes: *courses planned*, which might change over the planning period, and the student's final *courses scheduled*, which is the final set of courses saved before the rostering process begins. Course planning processes vary by district and school, with, for example, some schools asking students to independently request courses and others scheduling meetings between students and their counselors to plan courses together. To accommodate this variation, we combined saves by students, parents, and/or counselors to construct the measures of courses planned and scheduled. Based on the event log data on all courses planned and scheduled, we created indicators for whether students ever planned an advanced course in ELA and/or math and whether students ultimately scheduled an advanced course in ELA and/or math.

We tracked students' rostered courses, courses and credits attempted and earned, and daily attendance using gradebook and transcript data stored in the SIS for the 2024–25 school year, when students were expected to be in Grade 10. We received data on Grade 10 coursetaking outcomes in July 2025. To identify advanced courses rostered, attempted, and completed for each subject, we used the same process described above to clean and standardize the Grade 10 course names from the 2024–25 school year. We combined the advanced course list from randomization with the list from the 2024–25 school year to ensure consistent identification of advanced courses across time.

To address our fifth research question, we fielded a survey of counselors' experience with the tool through the SIS's user message boards and asked respondents if they would also complete an interview. The survey was administered from April 15–May 15, 2024; interviews were conducted from May 13–24, 2024. We received 33 survey responses and interviewed all five school staff who agreed to an interview.

Measures. We examined several coursetaking outcomes from both the course planning process and students' administrative records. From the planning process, we looked at whether students planned, scheduled, and/or rostered into an advanced ELA or math course.

Planned courses refer to courses saved to the student's course plan during any session over the planning period, which we defined as lasting from the first course planning activity in the 2023–24 school year through September 30, 2024. Planned courses gauge overall interest in courses and how interest may change over the planning period, even if students did not request a given course in their final course plan. We examined planned courses for Grade 10 and for Grade 11 to see whether the tool increased interest beyond the Grade 10 school year. We included Grade 11 courses planned when students were in/an either Grade 9 or Grade 10, although the notifications were only active when students were in Grade 9.[9] *Scheduled courses* refer to the most recently saved course plan before the planning period ended September 30, 2024, representing students' final course request in each subject. *Rostered courses* refer to the courses a student was enrolled in as of October 1, 2024. Rostered courses may differ from scheduled courses due to factors such as scheduling conflicts, class availability, or staff intervention during placement into classes. We examined scheduled and rostered courses for Grade 10 using student administrative data.[10]

We also examined students' continued enrollment in and completion of Grade 10 advanced courses using four outcomes: whether students remained enrolled in their advanced courses for the entire course period (*attempted a credit*), whether they earned a passing grade (D or higher) in the course (*earned a credit*), the number of ELA and math credits attempted and earned from advanced courses, the number of advanced ELA and math courses attempted and passed, and the proportion of advanced credits attempted and earned among all credits in ELA and math. Finally, we examined effects on students' attendance rate, given research indicating students in advanced courses may be more engaged (e.g., Kolluri, 2018).

We used the following student demographic characteristics as covariates in our analyses: race/ethnicity (membership in one of five mutually exclusive student racial/ethnic groups: Asian, Black, Hispanic, White, and Other), sex, EL status, and special education status. We included the following school- and district-level covariates in our models: school racial/ethnic composition, school size, and district locale type (which was also the

[9] Although the notifications were not active during students' Grade 10 school year, at many schools in our sample students review and update their Course Planner for more than one year at a time. This means that many students entered (or updated) not just their Grade 10 but also their Grades 11 and 12 courses in their Course Planner during their Grade 9 year. Specifically, 40 to 43 percent of all eligible students planned at least one Grade 11 course during their Grade 9 year. Of eligible students who used the course planner to schedule at least one Grade 10 course, 66 to 80 percent also planned at least one Grade 11 course during their Grade 9 year.
[10] The timeline of our grant and data sharing arrangement with the SIS provider did not allow us to examine outcomes beyond the 2024–25 school year. As a result, only Grade 11 outcome we were able to observe was courses planned, as Grade 11 course planning was complete by the end of the 2024–25 school year.

randomization block) at the time of randomization, and the number of unique advanced courses taken by Grade 10 students in a given school in the 2023-24 school year. We also examined heterogeneity in treatment effects by student race/ethnicity, sex, EL status, and special education status, as well as by school composition, school size, and district locale.

Analytic Approach. We estimated the impact of the automatic notification tool on student course planning and scheduling, course enrollment, and completion of advanced courses using an intent-to-treat (ITT) analysis. For binary outcomes, we estimated the following two-level logit model with random intercepts and fixed slopes:

$$P(Y_{is} = 1) = logit^{-1}(\gamma_{00} + \gamma_{01}Treat1_s + \gamma_{02}Treat2_s + \boldsymbol{\gamma_{03}}School_s + \boldsymbol{\theta}_s + \boldsymbol{\gamma_{10}}Student_{is} + u_s) \quad \text{(Eq. 1)}$$

Y_{is} is the probability of a given outcome for student i in school s. γ_{00} is the adjusted average outcome for control schools. $Treat1_s$ and $Treat2_s$ are indicator variables for treatment status (coded 1 if school s is in a given treatment group and 0 otherwise). The key parameters of interest are γ_{01} and γ_{02}. γ_{01} is the difference between T1 and control schools in the student outcome and γ_{02} is the difference between T2 and control schools in the student outcome. $School_s$ represents a vector of school characteristics. $\boldsymbol{\gamma}_{03}$ is a vector of coefficients of the average relationships between school characteristics and student outcomes across all schools. θ_s is a vector of randomization block fixed effects. They represent differences among control schools across locale types, with suburban as the reference category. $Student_{is}$ is a vector of student-level characteristics including race/ethnicity, sex, EL status, special education status, and prior math and ELA course grades, and γ_{10} is the pooled average relationship between student characteristics and student outcomes across all schools. Finally, u_{0s} is a random error associated with school s. For continuous outcomes (number of credits, number of courses, and proportion of courses), we estimated an analogous two-level linear regression model with random intercepts and fixed slopes. We examined student-level heterogeneity in T1 and T2 effects by interacting the treatment indicators with student demographic variables. We also examined school- and district-level heterogeneity by interacting the treatment indicators with school characteristics (racial/ethnic composition, number of Grades 9 and 10 students), and district locale (urban, suburban, town, or rural).

We examined each outcome for "any" advanced course in either math or ELA and separately for math and ELA. Analyses for any advanced course used the pooled sample of students eligible for either a math or an ELA notification (or both); analyses for math and ELA used the sample of students eligible in the focal subject. We analyzed each outcome using all students in the relevant analytic sample with data on that outcome. We used listwise deletion for the relatively small number of students missing covariate data (see Table 2).

Supplemental Analysis – Propensity Score Matching. To conduct typical treatment on the treated (TOT) analyses using an instrumental variables design, we would need variation within both the treatment and control conditions in receipt of the treatment to serve as a first-stage instrument. This approach was not feasible for this study because no students in the control condition were sent a notification. Instead, to estimate causal effects of receiving the full treatment (that is, logging in, seeing the alert, and clicking on the alert to view the full notification text), we conducted a supplemental propensity score analysis of the TOT effect for the subset of students who had at least one user click on the alert to view the notification text. We conducted propensity score matching to create a matched sample of students in each treatment group with students in the control group who ever logged into the Course Planner and who had similar probabilities of clicking on the alert based on their baseline demographic and academic characteristics. Details of our propensity score matching analytic approach and results from balance checks before and after matching are in the appendix materials and Appendix Table A5.

Attrition and Joiners. Several characteristics of the study design and the intervention design make it unlikely that either attrition or sample joiners would be influenced by the intervention. First, random assignment occurred at the school level while the unit of measurement is students. Students are unlikely to switch schools to either receive or avoid receiving an alert in their Course Planner. Second, the intervention is light-touch and has low visibility, so students are unaware of the treatment until they log into their course planner—and even then may not know they are receiving a treatment unless they know the notifications are not typically part of the Course Planner. Despite the low risk of bias from students who entered the school after random assignment (i.e., joiners), we chose to exclude these students from our analyses. Because of the low probability that the nature of the treatment was related to students' decisions to leave a school and our use of administrative data to measure all outcomes, we used the optimistic attrition boundary to assess attrition (WWC, 2022).

One district withdrew their consent to allow the study team to use their data after randomization but before data collection was completed (see Table 2). The district's four schools were removed from the sample; two of the schools were in the control group, one was in T1, and one was in T2. An additional three schools, one in each condition, did not have the necessary covariate data. The final sample for the ITT analyses included 103 schools

(34 in T1; 35 in T2; 34 in control). Six schools in T1, five schools in T2, and three schools in the control group ended the 2023–24 school year with no event log data, meaning that despite having used the Course Planner for at least 70 percent of their Grade 9 students in 2022–23, they did not use the Course Planner with any Grade 9 students in 2023–24 (see Table 2). Rather than treat these schools as attrition, students in these schools were considered to have low (zero) implementation fidelity, and their values for the outcomes of advanced courses planned and scheduled were coded as 0 (did not plan/schedule an advanced course).

The overall cluster-level attrition rate was 6.4 percent, and the differential cluster-level attrition rate, calculated as the largest percentage difference between any two of the three treatment arms, was below the maximum threshold allowed under the optimistic boundary, indicating low cluster-level attrition (Appendix Table A2; WWC, 2022). We assessed individual-level attrition using students in non-attriting clusters at follow-up. The individual-level attrition rate was 14.6 percent for Grade 10 advanced courses planned and scheduled; 15.5 percent for advanced courses rostered; 15.8 percent for advanced courses and credits attempted and passed and for daily attendance rates; and 15.0% for Grade 11 courses planned and scheduled (Appendix Table A2). For all outcomes, the highest differential attrition rate was within acceptable standards for the optimistic boundary, allowing the study and all ITT outcomes to meet WWC standards without reservations (Appendix Table A3; WWC, 2022). In all analyses, we adjusted for student, school, and district-level covariates.

Results

In this section, we first present the impact results organized by outcome (RQs 1 and 2). We present the estimated effects as percentage point differences for binary outcomes and Hedges's *g* for continuous outcomes. We focus on results that are statistically significant, substantively meaningful (which we define as effects of 5 percentage points or larger for binary outcomes or a Hedge's g of > .20 for continuous outcomes), or both. We then report results from our exploratory analyses of estimated effect heterogeneity by student, school, and district characteristics (RQ3), and exploratory analyses and qualitative findings about use of the notification tool in the two treatment groups (RQs 4 and 5). We also report results from a supplementary PSM analysis examining effects for the subgroup of students in T1 and T2 who clicked on the notification, compared with matched control group students and conclude by contextualizing impact results with findings from counselor surveys and interviews.

Impacts on Coursetaking (RQs 1 and 2)

Planned or Scheduled an Advanced Course. We found no significant ITT effects of either T1 or T2 on planning or scheduling advanced Grade 10 courses in the Course Planner (Table 3, Figure 4), although overall students in both treatment conditions were less likely to plan or schedule an advanced course. However, we find large and statistically significant effects of planning Grade 11 courses. Students in T1 were 22 percentage points more likely to plan any advanced course, 13 percentage points more likely to plan an advanced ELA course, and 24 percentage points more likely to plan an advanced math course for Grade 11 than students in the control condition. Similarly, students in T2 were 24 percentage points more likely to plan any advanced Grade 11 course and 24 percentage points more likely to plan an advanced math course than students in the control condition. Students in T2 were also 8 percentage points more likely to plan an advanced Grade 11 ELA course; however, this difference was not statistically significant.

Course Enrollment. We found no significant ITT effects of either T1 or T2 on whether students rostered into advanced Grade 10 courses (see Table 3 and Figure 5). Students in T2 were 7 percentage points less likely to be rostered into an advanced ELA course than students in the control condition, but while this difference is substantively meaningful, it is not statistically significant.

Courses Attempted and Completed, Credits Attempted and Completed, and Attendance. Across all measures of Grade 10 courses attempted and completed, we found no significant differences between students in either T1 or T2 compared to students in the control group (see Table 3). Students in T1 were about 9 percentage points more likely than students in the control condition to both attempt and complete an advanced ELA course—a substantive but not statistically significant difference (Figure 6). There were no ITT effects on the number of advanced courses or credits attempted or completed, overall or as a percentage of all core credits earned, or on students' daily attendance rates.

Differences between Treatment Groups. None of the T1 notification tool effects differed significantly from the T2 effects (we report mean values for T1 and T2 in Table 3 and conducted statistical tests of the mean differences). ITT effects were substantively (but not significantly) larger for students in T1 than T2 for the following outcomes: rostering into an advanced ELA course (a 7 percentage point difference), attempting at least one advanced ELA course (a 6 percentage point difference), and passing any Grade 10 advanced course and at least one Grade 10 ELA course (both a 5 percentage point difference).

Heterogeneity of Treatment Effects (RQ 3). Given the main effects findings, we examined heterogeneity of treatment effects for a limited set of outcomes: planned any advanced course for Grade 10 or Grade 11, scheduled any advanced course for Grade 10, rostered into any advanced course in Grade 10, and attempted and passed any advanced course in Grade 10. We examined the interactions between students' race/ethnicity, sex, special education status, EL status, and prior course grades; school composition; and district locale and each treatment condition. Table 4 presents impacts for subgroups relative to subgroup peers in the control condition (i.e., Asian students in T1 vs. Asian students in C), as well as differential impacts between subgroups in the same treatment condition (i.e., EL vs Not-EL in T1). For each covariate except prior ELA and math course grades, the effects of both T1 and T2 on Grade 11 courses planned were large and statistically significant, and the effects did not differ significantly by subgroup (Table 4). In the following paragraphs we discuss heterogeneity in Grade 10 outcomes.

Several effects on Grade 10 outcomes were substantively meaningful within racial/ethnic groups, but none were statistically significant: Black students in T1 and T2 were 6 percentage points less likely to plan or schedule any advanced course than Black students in the control condition (Table 4 and Appendix Figures A1 and A2). White students in T1 were 5 percentage points less likely to schedule an advanced course than White students in the control condition. The effect of both T1 and T2 on the probability of rostering into an advanced course was 5 percentage points larger for Black students than for White students. Hispanic students in T1 were 5 percentage points less likely to plan or schedule any advanced course than Hispanic students in the control condition. The effect of T2 on the probability of rostering into any advanced course was 6 percentage points larger for Hispanic students than for White students. Asian students in T1 were 5 percentage points less likely to plan and Asian students in T2 were 5 percentage points less likely to schedule an advanced course than Asian students in the control condition.

EL students in T1 were substantively but not significantly less likely to roster into any advanced course than EL students in the control condition (7 percentage points; Appendix Figure A3). However, T1 had large, significant positive effects on EL students' probability of attempting and passing any advanced course (both 14 percentage points; $p<.001$; Appendix Figure A4). T2 also had substantively positive, but not significant, effect on EL students' probability of attempting (10 percentage points) and passing (10 percentage points) any advanced course compared with EL students in the control condition. The effects of T1 were substantively and significantly larger for EL students than non-EL students for courses planned (9 percentage point difference; $p<.01$), scheduled (8 percentage point difference ($p<.01$), attempted (10 percentage point difference; $p<.01$), and completed (10 percentage point difference, p<.01). Similarly, the effects of T2 were substantively and significantly larger for EL students than non-EL students for courses planned (6 percentage points; p<.05), attempted (11 percentage points; p<.05), and completed (11 percentage points; p<.05), and substantively larger for courses scheduled (6 percentage points).

Students with IEPs in T2 were 8 percentage points more likely to roster into any advanced course than students with IEPs in the control condition. We also observed a larger effect of T2 on rostering into any advanced course (7 percentage points) and of T1 on scheduling any advanced course (5 percentage points) for students with IEPs than students without IEPs, although these differences were not statistically significant.

The effect of T1 on planning and scheduling an advanced course was significantly larger among students with higher prior ELA and math course grades (4–6 percentage points; p<.01), and the effect of T1 on attempting and passing any advanced course was significantly larger among students with higher prior math course grades (3 percentage points; p<.05). In contrast, the effect of T2 on rostering into any advanced course was 3 percentage points smaller among students with higher prior math course grades (p<.01).

Looking at treatment variation by school characteristics, the effects of T1 on planning and rostering into any advanced course decreased as the percentage of Black and Hispanic students in the school increased (Table 4). The effects of T1 and T2 did not vary by school size, and we found mixed results on the effects of T1 and T2 on outcomes by school locale type, with the largest effect sizes concentrated among Grade 10 advanced courses planned and scheduled and Grade 11 advanced courses planned (Table 4 and Figure A5).

Notification Tool Usage. Students, parents, and school counselors engaged with the tool at low rates, indicating low implementation fidelity. In this section, we describe tool usage patterns and associations between tool usage and course outcomes. We then report findings from the PSM analyses estimating a TOT effect for students who had at least one student, parent, or counselor view of the notification text. We end by contextualizing the quantitative findings using information from the school counselor surveys and interviews.

Notification Tool Usage and Course Outcomes (RQ4). For users in the treatment conditions to fully engage with the notification tool as intended, two steps had to occur. First, a user affiliated with an eligible student had to log into the Course Planner at least once during the 2023–24 school year. Upon the first login and on every subsequent login at which students had not yet planned an advanced math and/or ELA course, the Course Planner displayed a clickable course planning recommendation alert below the math and/or ELA course selection fields (see Figure 2). Second, a user had to click on the course planning recommendation to view the full notification text (see Figure 3).

During the 2023–24 school year, 71 percent of eligible students in T1 and 72 percent of eligible students in T2 had any user log in to the Course Planner, which completed Step 1 to activate the Course Planner recommendation alert (Appendix Table A4). In the control condition, 69 percent of eligible students had any user log in, although for these students a login did not activate an alert. Across conditions, school staff were most likely to log in to the Course Planner, with 58–68 percent of students having at least one counselor log in to their Course Planner. About a third of students had any Course Planner login (35–40 across conditions). Only 7–10 percent of students had a parent log in to the Course Planner during the course planning window in the 2023-24 school year.

Some students were eligible for a notification only in ELA, some only in math, and some were eligible in both subjects. Once users in the treatment conditions logged in, they could see the alert(s) that applied to them based on their eligibility. In our sample of eligible students, 88 to 89 percent were eligible for an ELA notification, but 52 to 55 percent of students eligible for an ELA notification saw the ELA course recommendation alert due to the lower rates of user logins (no students in the control condition were sent ELA notifications). Of students who completed Step 1 (logging into the course planner) to see the ELA course planner recommendation alert, 6 percent of T1 students and 10 percent of T2 students completed Step 2 (had any user click on the alert to view the full notification text). Students were most likely user type to click on the alert: 4 percent of students in T1 and 7 percent of students in T2 clicked on their ELA alert and viewed the ELA notification.

The trends were similar for math, with somewhat lower rates of eligibility for a math notification and similar notification view rates. In our sample of all eligible students, 79 to 81 percent were eligible for a math notification, and 50 to 52 percent of students in the treatment conditions who were eligible for a math notification ended up seeing the math course recommendation alert, again due to lower rates of user logins. Of students who completed Step 1 to see the math course planner recommendation alert, 6 percent of T1 students and 11 percent of T2 students had any user click on the alert to view the full notification text. Students again were the most likely user type to click on the math alert: 4 percent of students in T1 and 8 percent of students in T2 clicked on their math alert and viewed the math notification. Only about 1–2 percent of parents and school counselors clicked on either alert to view the full notification text. Across users who did click on the notification, the median view times of 16–17 seconds were sufficient to read the full text.

Descriptive Outcome Patterns by Tool Usage. In both treatment conditions, rates of rostering into, attempting, and completing any advanced course were substantially higher among students who ever logged into the course planner and saw the alert (or had a parent or counselor log in) than students who never had a login and therefore never saw the alert. Of students in T1 with no login, 38 percent rostered into an advanced course, compared with 48 percent of students with a login and subsequent click on the alert and 62 percent of students with a login but no click on the alert (Table 5). Differences were even larger for students in T2: the probability of rostering into an advanced course was 63 and 67 percent for T2 students who ever logged in and either clicked or did not click on the alert, respectively, and 28 percent for those who never logged in. Students in T1 with a login also had higher rates of attempting and passing any advanced course (45 to 49 percent compared with 41 percent); in T2 the differences were again larger, with 43 to 52 percent of students in T2 attempting and passing any advanced course compared with 26 to 27 percent of students with no login.[11]

We can also compare rates of planning and scheduling advanced courses among treatment students who completed only Step 1 as compared to students who completed Steps 1 and 2. Students who had any user complete both Step 1 (logging in) and Step 2 (clicking on the course recommender alert to view the full notification text) were more likely than those who only completed Step 1 to plan at least one advanced course (50 percent vs. 35 percent of T1 students, and 47 percent vs. 39 percent of T2 students; Table 5) and to ultimately schedule at least one advanced course (49 percent vs. 34 percent of T1 students, and 44 percent vs. 37 percent of T2 students). Rates of attempting an advanced course also differed substantively for students in T2 who clicked as compared to those who did not (52 percent vs. 44 percent). Rates of passing an advanced course were about 8 percentage points higher (51 vs 43 percentage points) for students in T2 who clicked on the alert than students who did not click. Interestingly, students in T1 with any user click had lower rates of initial rostering into any advanced course than students who had no user click (48 percent vs. 62 percent).

PSM Results: Effects of Clicking on the Alert to View the Notification Text. As expected, rates of planning and scheduling advanced courses were higher in the TOT samples

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[11] About 11 percent of T1 students and 6 percent of T2 students had at least one login to the course planner but did not receive an alert. Although we it is not possible to identify the reason for this on a student-by-student basis, we are aware of several conditions that would prevent an alert from appearing: students did not receive an alert if their school did not offer a relevant advanced course or if the student had not completed prerequisites for available advanced courses. Additionally, some schools or pathways pre-populated courses in the planner for students to review (an opt-out approach to course planning). If a student had a pre-populated advanced course in their planner in the subject(s) for which they were eligible, they would not receive an alert for the subject(s).

than the ITT sample, as the TOT samples were limited to treatment students who ever viewed the notification and matched comparison group students who ever logged in. Across TOT conditions, 46 to 51 percent of students planned any Grade 10 advanced course and 28 to 65 percent planned any Grade 11 advanced course (Table 6), compared with 28 to 33 percent of students who planned any Grade 10 advanced course and 24 to 48 percent who planned any Grade 11 advanced course across ITT conditions (see Table 3).

As in the ITT results, the TOT results show large, significant effects of viewing the notification text on Grade 11 advanced courses planned: the T1 effect of viewing the notification text on planning any advanced Grade 11 course was 37 percentage points, and the T2 effect was 33 percentage points (Table 6). The subject-specific effects of both T1 and T2 on planning Grade 11 advanced math courses were large and significant: 29 percentage points in T1 and 32 percentage points in T2 for math. Effects on planning Grade 11 advanced ELA courses were also substantively large: 11 percentage points in T1 and 19 percentage points in T2, though only the effect of T2 was significant. The effects of T1 and T2 on planning any Grade 11 advanced course and of T2 on planning an advanced Grade 11 math course were 9 to 15 percentage points larger than the already large effects in the ITT results. Similar to the ITT results, effects on Grade 10 outcomes were not statistically significant, though a number of effects changed substantively. Across treatment groups, the effects on Grade 10 ELA outcomes were generally similar or substantively smaller, whereas the effects on Grade 10 math outcomes were generally similar or substantively larger.

School Counselor Experience with the Notification Tool (RQ5). The low counselor view rates are reflected in the survey results, where more than half of survey respondents indicated they had not seen the notification, or that they saw the alert but did not click through to the notification text. The low rates could be driven by a few factors that surfaced in the interviews. First, the notification is likely to be most useful for students on the margin of advanced coursetaking—students who are closer to the eligibility threshold or who belong to groups historically underrepresented in advanced courses. As one counselor noted, “we didn't click the recommendation because nine times out of ten […] if that blue button was down there, those kids would probably already [be] recommended.” Additionally, this counselor’s statement indicates that once counselors viewed the notification for some students, they didn’t need to re-read the text to know what the alert indicated. Alternately, counselors may use the course planner differently than students: two interviewees noted their districts did not communicate with them about the tool so they didn’t know to look for it, although they did find it themselves or hear from students who saw it and asked about it.

Of survey respondents who recalled viewing the notification, two-thirds said at least a few students mentioned the notification to them, and more than two-thirds reported it influenced them to initiate conversations with students. Just over half reported the notifications changed their perspective about one or more students' ability to succeed in advanced courses. One interviewee stated:

> There were some [students] that kind of fall within the higher middle who we discussed it together. I said, "They're recommending you for this higher level class. Would you like to take the honors class?" Then we would talk about their grades […], and then I'd say, "Yeah, I think you could probably do the honors class and they're recommending you for that." We have a lower socioeconomic population. So I think seeing that, the students kind of felt good about themselves.

Another interviewee stated, "This particular student […], I would've never thought he would make scores to even be presented that opportunity that's like, oh, wait a minute, maybe I look at something here. We need to talk to him about reinforcing that he does have abilities that he may be questioning himself. For sure it did that."

Counselors who said the tool did not change their perspective reported either that the notification largely identified students they already would identify, or that they felt the recommendations were flawed in some way. For example, one interviewee said their school relies on teacher recommendations and teachers rely on grades, not assessments; in this school, some students had a proficient assessment score but decision makers felt their grades were too low to warrant consideration. This may reflect a limitation of implementing the tool at scale, as the identification algorithm cannot fully reflect each district's distinct processes and priorities. It also may reflect that the lighter-touch notification alone is not sufficient to overcome existing recommendation procedures.

Discussion and Conclusion

Automatic enrollment policies implemented in several states and districts show promise for increasing participation in advanced courses for students who are likely to succeed but may be overlooked using traditional identification methods (e.g., Austin et al., 2025). Embedding an automatic notification tool into course planning software used by many schools and districts across the country has the potential to rapidly scale the core components of this policy. Our findings demonstrate the potential and the limitations of such an approach.

Large, significant positive ITT effects of the notification tool on the proportion of students planning advanced courses for Grade 11 indicate that the tool was successful in shifting student interest toward advanced courses, though for later in high school than the notification targeted. The tool increased students' probability of planning any Grade 11 advanced course 22 to 24 percentage points, and effects were even larger in the PSM-based TOT analysis (37 and 33 percentage points for T1 and T2, respectively). In comparison, district-level automatic enrollment policies in Washington state increased any advanced course taking among eligible students in Grades 11 or 12 by 5 percentage points (Austin et al., 2025). While we cannot observe enrollment in Grade 11 courses, Grade 10 effects for rostering into, attempting, and completing any advanced course were 6 to 10 percentage points more positive in T1 and 4 to 7 percentage points more positive in T2 than effects for planning and scheduling any advanced course (see Table 3). If patterns were similar in Grade 11, the effects on advanced courses rostered into, attempted, and completed would be large.

Although the notification tool had larger effects for planning courses later in high school, it is still valuable to intervene early. One potential explanation for the patterns we see is that students not quite ready for a Grade 10 advanced course during the course planning period planned ahead for Grade 11 advanced courses instead, giving them something to work toward. Descriptively, more Grade 9 students in T1 and T2 planned a Grade 11 course of any type (advanced or not) than Grade 9 students in the control condition (77 and 80 percent, respectively, compared with 66 percent), supporting this hypothesis that the treatment increased longer-term planning. The substantively more positive effects on rostering, attempting, and completing Grade 10 advanced courses than planning and scheduling Grade 10 advanced course may also indicate that although students may initially did not choose a Grade 10 advanced course, they made changes between the course planning period and the beginning of Grade 10 that enabled them to move into an advanced course.

Based on coursetaking patterns identified in prior research, we expected the tool to have the largest effects on students near the threshold and students historically overlooked for advanced courses using conventional identification methods. The eligible student pool includes students well above the proficiency threshold as well as students near the cutoff; many students eligible for a notification likely were planning to take an advanced course regardless of the notification. However, high-performing students historically overlooked for advanced courses might be more responsive to the notification than other high-performing students. We found that the effect of T1 on planning, scheduling, attempting and passing any advanced course was higher for students with higher prior course grades, especially in math. Our qualitative findings indicate school counselors were skeptical of readiness if students' course grades were relatively low, even if their test scores indicated proficiency, so students with scores near the threshold may also have needed to demonstrate stronger course performance. We did find suggestive evidence that T1 had substantively meaningful ITT effects on attempting and passing advanced Grade 10 courses for Black students and for students who are English learners (including significant effects of T1 on attempting and passing any Grade 10 advanced course). We did not have a measure of economic disadvantage, but the larger effects for English learners could indicate larger effects for students whose parents are less able to support the course selection process.

Our finding that the effects of T1 decreased as the percentage of Black and Hispanic students in a school increased aligns with prior research indicating historically overlooked students are less likely to be overlooked in schools with larger percentages of Black and Hispanic students (Theokas & Saaris, 2013; Tyson, 2011). In such schools, we would expect to find fewer students who would benefit from the notification. Our finding that effects differed significantly by district locale also aligns with prior research indicating varying advanced course taking opportunities by locale (Price, 2021; Xu et al., 2021). However, the locale effects show different patterns across treatments and T2 did not have enough schools in towns with data to estimate differential effects for course planning and scheduling.

The notification tool was designed to integrate into the SIS's existing Course Planner module with no special action required by districts or schools. When treatment districts completed their monthly software updates in early fall 2023, the tool became active for the 2023–24 school year, as Grade 9 students planned their Grade 10 (and often Grades 11 and 12) courses for the 2024–25 school year. This represents the lowest-cost, most-scalable approach to implementing the tool, ensuring the notifications become part of the Course Planner experience for all districts using an SIS. However, there are tradeoffs to maximum scalability. While we did provide information to participating districts about the tool, its purpose, and its functionality, we also did not ask districts to take any action to let students, parents, or school counselors know about the tool. This likely led to lower awareness among our target users. For example, students and parents who didn't receive advanced notice to look for the notification may not have paid much attention to the course recommendation alert in their Course Planner and did not click on the alert to learn more; counselors used to moving quickly through the Course Planner for many students may not have clicked on alerts that weren't part of their usual procedure.

Our emphasis on low-touch scalability also meant that the tool operated within districts' existing, varying course planning processes. Our criteria for study inclusion required at least 70 percent of a school's students to have planned a course in the Course Planner during the year prior to implementation, but it appears that some districts' and schools' use of the Course Planner changed year-to-year, resulting in many students never receiving the treatment. Our ITT results therefore reflect effects under relatively low implementation fidelity. The propensity score results indicate the TOT effects may be even larger for Grade 11 planning, and may have larger effects for moving students into advanced math courses rather than advanced ELA courses.

Similarly, the tool operated within districts' course scheduling constraints. Automatic enrollment policies typically include proactive initiatives to expand advanced course offerings alongside increased identification of students eligible for those courses (although the extent to which course capacity increases following policy implementation is not well known). In our case, districts and schools may need to respond to increased interest in advanced courses between the course planning period and the beginning of the new school year. If districts are unable to quickly expand supply, increased interest resulting from the notification may not immediately translate into increased advanced coursetaking.

It is possible that our findings of smaller to null effects on Grade 10 course outcomes but large, significant effects on Grade 11 planning reflect constraints of operating the tool within districts' existing processes. For example, advanced course programs such as Advanced Placement typically offer more options for students in Grades 11 and 12 than students earlier in high school. If Grade 9 students are motivated to plan advanced courses but not enough seats are available in Grade 10 courses, their counselors may encourage them to plan a Grade 11 advanced course instead, either because more options are available or to allow the school time to adjust its course offerings to meet demand. Similarly, if the notification tool identifies students as eligible based on a proficient test score but the student's grades reflect lower performance, counselors may encourage students to select a non-advanced Grade 10 course and work hard to demonstrate readiness for advanced courses by Grade 11 based on the school's expectations of the student.

Our results point to several possible modifications to automatic notification that could result in larger effects across course outcomes. First, districts and schools could take steps to increase the tool's visibility by communicating with school counselors, students, and parents outside of the Course Planner. Schools could send an email, letter, or text message notification to students and their parents ahead of the start of their course planning window, encouraging them to log into their Course Planner to check for course recommendation notifications. Second, districts or schools could send an email to school counselors to ensure they are aware of the notification and which students will receive it, and provide guidance to counselors on how to incorporate discussion of the notification into their course planning conversations. Third, districts and schools could conduct a review of advanced course offerings and available seats, and identify ways to increase supply in courses for which the notification tool may increase demand. Hiring and training teachers who can teach advanced courses can be challenging, but some states offer financial supports to incentivize expanding advanced course offerings, especially as at least 35 states now have advanced coursework as a college and career readiness (CCR) accountability measure (Hyslop, 2025) Each of these modifications requires increased district and school involvement, which may reduce scalability; however, the presence of the notification tool within the SIS could provide motivation to implement these changes despite the absence of a formal academic acceleration/automatic enrollment policy. Further, the tradeoff of somewhat lower scalability for increased implementation fidelity may pay off in larger effects for districts and schools that take these steps.

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Tables

Table 1. Student and School Characteristics by Treatment Status

	T1	T2	Control	SMD T1–C	SMD T2–C
Number of schools	36	37	37	n/a	n/a
Number of students	7,831	8,166	8,860	n/a	n/a
Student characteristics (2023–24)					
White	0.39	0.40	0.41	-0.04	-0.03
Hispanic	0.20	0.23	0.22	-0.04	0.04
Black	0.31	0.27	0.29	0.06	-0.03
Asian	0.04	0.04	0.03	0.06	0.06
Other race/ethnicity	0.05	0.06	0.06	-0.01	0.01
Non-male	0.52	0.52	0.52	0.01	0.01
English learner	0.05	0.06	0.07	-0.05	-0.03
Has an Individualized Education Program (IEP)	0.07	0.09	0.06	0.02	0.08
Number of students	7,831	8,166	8,860	NA	NA
School characteristics (2022–23)					
Average Grade 10 enrollment	338 (196)	308 (157)	366 (164)	-0.15	-0.36
Proportion of students enrolled in an advanced ELA course in Grade 10	0.30	0.25	0.24	0.25	0.04
Proportion of students enrolled in an advanced math course in Grade 10	0.22	0.20	0.20	0.09	-0.00
Proportions of Students enrolled in any advanced Grade 10 course (2022–23)					
Proportion of all students	0.33	0.31	0.29	0.16	0.07
Proportion of Black students	0.25	0.24	0.22	0.12	0.08
Proportion of Hispanic students	0.31	0.27	0.25	0.21	0.07
Proportion of White students	0.36	0.33	0.32	0.14	0.06
Number of schools	36	37	36	NA	NA

Note. This table displays summary statistics. T1 = Treatment 1, T2 = Treatment 2, C = Control, SMD = Standardized Mean Difference.

Table 2. Attrition Progression by Treatment Condition

	T1	T2	Control	Total
Schools randomized	36	37	37	110
Students randomized	7,831	8,166	8,860	24,857
Schools dropped out before data collection	1	1	2	4
Schools remaining	35	36	35	106
Students remaining	7,609	8,012	8,627	24,248
Schools without covariate data	1	1	1	3
Schools remaining	34	35	34	103
Students remaining	7,317	7,766	8,457	23,540
Of remaining schools, students without covariate data	100	442	576	1,118
Students remaining	7,217	7,324	7,881	22,422
Analytic Samples				
Students without transcript data	794	833	963	2,590
Transcript data analytic sample	**6,423**	**6,491**	**6,918**	**19,832**
Students without roster data	*777*	*814*	*947*	*2,538*
Roster data analytic sample	**6,440**	**6,510**	**6,934**	**19,884**
Schools without grade 10 event log data due to non-takeup	6	5	3	14
Students without grade 10 event log data due to non-takeup, including those in schools with non-takeup	2,239	2,389	1,966	6,594
Students without grade 10 event log data due to attrition	*707*	*744*	*858*	*2,309*
Grade 10 event log data analytic sample	**6,510**	**6,580**	**7,023**	**20,113**
Schools without grade 11 event log data due to non-takeup	2	4	4	10
Students without grade 11 event log data due to non-takeup, including those in schools with non-takeup	1,631	2,145	3,459	7,235
Students without grade 11 event log data due to attrition	*742*	*770*	*894*	*2,406*
Grade 11 event log data analytic sample	**6,475**	**6,554**	**6,987**	**20,016**

Note. Sources of attrition are italicized. Analytic sample sizes are in bold. Schools and students who were missing event log data because they did not use the Course Planner to plan and schedule courses are not considered as attrition, but rather non-takeup of the treatment (WWC, 2022). Students who were missing event log data because they left the sample (e.g., moved out of the district) are considered as attrition.

Table 3. Overall Intent-To-Treat Effects of the Automatic Notification Tool

				Treatment 1 Effects			Treatment 2 Effects				
	T1 Mean	T2 Mean	C Mean	Mean Diff T1 v. C	SE	Cox/ Hedges g	Mean Diff T2 v. C	SE	Cox/ Hedges g	N Students	N Schools
Binary outcomes											
Any advanced course											
Planned any Grade 10 advanced course	0.28	0.29	0.33	-0.05	0.06	-0.15	-0.04	0.06	-0.12	20,113	103
Scheduled any Grade 10 advanced course	0.28	0.28	0.33	-0.05	0.06	-0.15	-0.05	0.06	-0.14	20,113	103
Rostered into any Grade 10 advanced course	0.61	0.61	0.60	0.01	0.05	0.04	0.02	0.05	0.04	19,884	103
Attempted any Grade 10 advanced course	0.50	0.46	0.46	0.04	0.05	0.10	0.00	0.04	-0.01	19,832	103
Passed any Grade 10 advanced course	0.50	0.45	0.45	0.05	0.05	0.11	0.00	0.04	-0.01	19,832	103
Planned any Grade 11 advanced course	0.46	0.48	0.24	0.22***	0.07	0.61	0.24***	0.07	0.66	20,016	103
Advanced ELA											
Planned a Grade 10 advanced ELA course	0.26	0.28	0.28	-0.02	0.06	-0.05	0.00	0.06	-0.01	17,417	100
Scheduled a Grade 10 advanced ELA course	0.26	0.26	0.28	-0.02	0.06	-0.06	-0.01	0.05	-0.03	17,417	100
Rostered into a Grade 10 advanced ELA course	0.42	0.35	0.43	-0.01	0.05	-0.02	-0.07	0.05	-0.19	17,224	100
Attempted a Grade 10 advanced ELA course	0.47	0.41	0.38	0.09	0.06	0.22	0.03	0.05	0.09	17,180	100
Passed a Grade 10 advanced ELA course	0.46	0.41	0.37	0.09	0.06	0.22	0.03	0.05	0.08	17,180	100
Planned a Grade 11 advanced ELA course	0.28	0.24	0.16	0.13*	0.05	0.46	0.08	0.05	0.32	17,337	100
Advanced math											
Planned a Grade 10 advanced math course	0.24	0.21	0.28	-0.04	0.05	-0.12	-0.07	0.05	-0.23	16,210	98
Scheduled a Grade 10 advanced math course	0.23	0.21	0.28	-0.05	0.05	-0.16	-0.07	0.05	-0.23	16,210	98
Rostered into a Grade 10 advanced math course	0.52	0.54	0.51	0.01	0.06	0.03	0.02	0.06	0.06	16,031	98
Attempted a Grade 10 advanced math course	0.40	0.38	0.39	0.01	0.05	0.03	-0.01	0.05	-0.03	15,997	98
Passed a Grade 10 advanced math course	0.39	0.37	0.38	0.01	0.05	0.03	-0.01	0.05	-0.02	15,997	98
Planned a Grade 11 advanced math course	0.42	0.41	0.18	0.24***	0.06	0.74	0.23***	0.06	0.72	16,132	98
Continuous outcomes											
Any advanced course											

	T1 Mean	T2 Mean	C Mean	Treatment 1 Effects: Mean Diff T1 v. C	SE	Cox/ Hedges g	Treatment 2 Effects: Mean Diff T2 v. C	SE	Cox/ Hedges g	N Students	N Schools
Number of adv. math/ELA credits attempted	0.82	0.79	0.77	0.05	0.08	0.05	0.02	0.09	0.02	19,832	103
Number of adv. math/ELA credits earned	0.81	0.77	0.75	0.06	0.08	0.06	0.02	0.09	0.02	19,832	103
Adv. math/ELA credits attempted as percent of all core credits earned	10.60	9.07	8.95	1.64	0.11	0.14	0.12	0.10	0.01	19,832	103
Adv. math/ELA credits earned as percent of all core credits earned	10.59	9.04	8.92	1.67	0.10	0.14	0.12	0.10	0.01	19,783	103
Number of adv. math/ELA courses attempted	1.24	1.00	1.14	0.10	0.10	0.06	-0.14	0.09	-0.10	19,832	103
Number of adv. math/ELA courses passed	1.23	0.99	1.13	0.10	0.10	0.07	-0.14	0.09	-0.10	19,832	103
Advanced ELA											
Number of adv. ELA credits attempted	0.46	0.47	0.42	0.03	0.09	0.06	0.05	0.09	0.08	17,180	100
Number of adv. ELA credits earned	0.45	0.46	0.42	0.04	0.09	0.06	0.04	0.09	0.07	17,180	100
Adv. ELA credits attempted as percent of all core credits earned	5.87	5.28	4.77	1.10	0.11	0.17	0.51	0.11	0.08	17,180	100
Adv. ELA credits earned as percent of all core credits earned	5.87	5.26	4.78	1.10	0.11	0.17	0.49	0.11	0.08	17,140	100
Number of adv. ELA courses attempted	0.70	0.58	0.61	0.09	0.11	0.11	-0.03	0.10	-0.03	17,180	100
Number of adv. ELA courses passed	0.69	0.57	0.60	0.09	0.11	0.11	-0.03	0.10	-0.04	17,180	100
Advanced math											
Number of adv. math credits attempted	0.45	0.43	0.42	0.03	0.07	0.05	0.01	0.07	0.01	15,997	98
Number of adv. math credits earned	0.45	0.43	0.42	0.03	0.07	0.05	0.01	0.07	0.01	15,997	98
Adv. math credits attempted as percent of all core credits earned	5.82	5.17	5.02	0.80	0.09	0.11	0.15	0.08	0.02	15,997	98
Adv. math credits earned as percent of all core credits earned	5.82	5.17	5.02	0.80	0.09	0.11	0.15	0.08	0.02	15,967	98
Number of adv. math courses attempted	0.67	0.58	0.63	0.04	0.09	0.04	-0.06	0.08	-0.06	15,997	98
Number of adv. math courses passed	0.67	0.57	0.63	0.04	0.09	0.04	-0.05	0.08	-0.06	15,997	98
Daily attendance rate	93.84	93.43	93.51	0.33	0.06	0.05	-0.09	0.05	-0.01	19,432	103

Note. T1 = Treatment 1. T2 = Treatment 2. C = Control. SE = standard error. Adv. = advanced. Effect sizes are reported in the Cox index for binary outcomes and as Hedges g for continuous outcomes.

Table 4. Effect Heterogeneity – Interaction Results for Any Advanced Course Outcomes

	Treatment 1						Treatment 2					
	Gr. 10 Outcomes					Gr. 11	Gr. 10 Outcomes					Gr. 11
	Plan	Schedule	Roster	Attempt	Pass	Plan	Plan	Schedule	Roster	Attempt	Pass	Plan
Student-level interactions												
White	-0.04	-0.05	-0.01	0.04	0.04	0.21**	-0.03	-0.04	-0.01	0.00	-0.01	0.25***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)
Black	-0.06	-0.06	0.04	0.05	0.06	0.23***	-0.06	-0.06	0.04	0.00	0.00	0.22***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.07)
Hispanic	-0.05	-0.05	0.00	0.03	0.04	0.24***	-0.02	-0.04	0.04	0.00	0.00	0.25***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	(0.04)	0.07
Asian	-0.05	-0.04	0.03	0.02	0.01	0.25**	-0.04	-0.05	0.00	-0.03	-0.03	0.24**
	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	0.08	0.07	0.06	0.06	0.06	0.08
Hisp.-White diff.	*0.00*	*-0.01*	*0.01*	*-0.01*	*-0.01*	*0.04*	*0.01*	*0.01*	*0.06*	*0.01*	*0.01*	*0.01*
Black-White diff.	*-0.02*	*-0.02*	*0.05*	*0.01*	*0.01*	*0.02*	*-0.02*	*-0.02*	*0.05*	*0.00*	*0.01*	*-0.02*
Asian-White diff.	*-0.01*	*0.01*	*0.04*	*-0.02*	*-0.03*	*0.05*	*-0.01*	*0.00*	*0.01*	*-0.03*	*-0.02*	*-0.01*
Male	-0.06	-0.06	0.02	0.04	0.04	0.22**	-0.05	-0.06	0.03	-0.01	-0.01	0.24***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.07)
Female	-0.04	-0.04	0.01	0.04	0.05	0.23***	-0.04	-0.04	0.00	0.01	0.00	0.24***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.07)
Female-Male diff.	*0.02*	*0.02*	*-0.02*	*0.01*	*0.00*	*0.00*	*0.01*	*0.01*	*-0.03*	*0.02*	*0.01*	*0.00*
Not an EL student	-0.06	-0.06	0.02	0.04	0.04	0.22**	-0.05	-0.05	0.02	-0.01	-0.01	0.24***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.07)
EL student	0.03	0.03	-0.07	0.14**	0.14**	0.23**	0.02	0.00	0.01	0.10	0.10	0.27**
	(0.05)	(0.05)	(0.08)	(0.05)	(0.05)	(0.07)	(0.05)	(0.04)	(0.11)	(0.05)	(0.06)	(0.08)
EL-Not EL diff.	*0.09***	*0.08***	*-0.09*	*0.10***	*0.10***	*0.01*	*0.06**	*0.06*	*-0.01*	*0.11**	*0.11**	*0.03*
No IEP	-0.05	-0.05	0.01	0.04	0.05	0.22**	-0.04	-0.05	0.01	0.00	-0.01	0.24***
	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.07)
Has an IEP	-0.02	0.00	0.02	0.03	0.04	0.22**	-0.01	-0.01	0.08	0.02	0.03	0.25***
	(0.05)	(0.04)	(0.08)	(0.05)	(0.05)	(0.07)	(0.05)	(0.04)	(0.07)	(0.05)	(0.04)	(0.07)
IEP-No IEP diff.	*0.03*	*0.05*	*0.01*	*-0.01*	*-0.01*	*-0.01*	*0.03*	*0.04*	*0.07*	*0.03*	*0.03*	*0.01*

	Treatment 1						Treatment 2					
	Gr. 10 Outcomes					Gr. 11	Gr. 10 Outcomes					Gr. 11
	Plan	Schedule	Roster	Attempt	Pass	Plan	Plan	Schedule	Roster	Attempt	Pass	Plan
Prior ELA grade	0.05**	0.06**	0.00	0.03	0.03	0.01	0.01	0.01	-0.02	0.01	0.01	-0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Prior math grade	0.05**	0.04**	0.00	0.03*	0.03*	0.01	0.00	0.00	-0.03**	0.00	0.000	-0.02
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
School-level interactions												
School size	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
School composition	-0.05***	-0.05***	0.01	-0.01	-0.01	-0.03	0.00	0.00	0.00	-0.01	-0.01	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
District locale interactions												
Suburb	0.02	0.02	-0.01	0.07	0.07	0.32**	-0.03	-0.03	-0.16*	-0.13	-0.12	0.16
	(0.12)	(0.12)	(0.09)	(0.09)	(0.09)	(0.11)	(0.11)	(0.11)	(0.08)	(0.07)	(0.07)	(0.10)
Town	0.33*	0.31*	0.06	0.12	0.11	0.06	--	--	-0.04	0.09	0.09	--
	(0.15)	(0.15)	(0.09)	(0.18)	(0.18)	(0.19)	--	--	(0.09)	(0.19)	(0.19)	--
Rural	0.02	0.02	0.06	-0.09	-0.09	0.38***	-0.07	-0.08	0.06	0.05	0.04	0.24
	(0.09)	(0.09)	(0.08)	(0.07)	(0.07)	(0.09)	(0.12)	(0.12)	(0.09)	(0.08)	(0.07)	(0.13)
City	-0.23**	-0.23**	-0.01	0.08	0.10	0.05	0.00	-0.02	0.20*	0.07	0.08	0.45*
	(0.07)	(0.07)	(0.11)	(0.08)	(0.08)	(0.10)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.10)
Suburb-Town diff.	*-0.31*	*-0.30*	*-0.07*	*-0.05*	*-0.04*	*0.25*	*0.08*	*0.08*	*-0.13*	*-0.22*	*-0.21*	*0.27*
Suburb-Rural diff.	*-0.01*	*-0.01*	*-0.07*	*0.16*	*0.16*	*-0.07*	*0.04*	*0.05*	*-0.23*	*-0.17*	*-0.16*	*-0.08*
Suburb-City diff.	*0.25*	*0.24*	*0.00*	*-0.01*	*-0.03*	*0.26*	*-0.03*	*-0.02*	*-0.36***	*-0.19*	*-0.20*	*-0.29**

Note. Standard errors are in parentheses. *p < 0.05, **p<0.01, ***p < .001. For binary outcomes, table reports marginal effects of each treatment by student characteristic and differences in marginal effects between groups of students. For continuous outcomes, table reports coefficient from interactions between covariate and treatment condition. In the T2 condition, there was not enough variation in courses planned and scheduled in schools located in towns to estimate interactions between treatment and town locale. Prior grades are on a continuous scale of 60 to 100 and have been grand mean centered.

Table 5. Advanced Course Planning, Enrollment, and Completion by Level of Interaction with the Planner

	T1: Ever logged in (n=5,598) Any user click (n=369)	T1: Ever logged in (n=5,598) Received alert, no user click (n=4,386)	T1: Ever logged in (n=5,598) Did not receive alert (n=843)	T1: Never logged in (n=2,233)	T2: Ever logged in (n=5,880) Any user click (n=674)	T2: Ever logged in (n=5,880) Received alert, no user click (n=4,682)	T2: Ever logged in (n=5,880) Did not receive alert (n=524)	T2: Never logged in (n=2,286)
Grade 10 outcomes – proportions of students with:								
Any advanced course planned	0.50	0.35	0.45	N/A	0.47	0.39	0.25	N/A
At least one advanced ELA course planned	0.44	0.31	0.40	N/A	0.40	0.32	0.21	N/A
At least one advanced math course planned	0.36	0.25	0.37	N/A	0.27	0.22	0.11	N/A
Any advanced course scheduled	0.49	0.34	0.45	N/A	0.44	0.37	0.24	N/A
At least one advanced ELA course scheduled	0.44	0.30	0.39	N/A	0.35	0.30	0.21	N/A
At least one advanced math course scheduled	0.34	0.24	0.37	N/A	0.25	0.21	0.11	N/A
Any advanced course rostered	0.48	0.62	0.63	0.38	0.63	0.67	0.57	0.28
At least one advanced ELA course rostered	0.34	0.36	0.47	0.32	0.38	0.36	0.32	0.16
At least one advanced math course rostered	0.36	0.54	0.49	0.28	0.50	0.56	0.45	0.20
Any advanced course attempted	0.49	0.46	0.53	0.41	0.52	0.44	0.35	0.27
At least one advanced ELA course attempted	0.43	0.39	0.47	0.39	0.41	0.36	0.31	0.23
At least one advanced math course attempted	0.33	0.33	0.41	0.30	0.36	0.30	0.21	0.15
Any advanced course passed	0.49	0.45	0.53	0.41	0.51	0.43	0.35	0.26
At least one advanced ELA course passed	0.42	0.39	0.46	0.39	0.40	0.35	0.31	0.23
At least one advanced math course passed	0.33	0.33	0.41	0.30	0.36	0.30	0.21	0.15
Grade 11 outcomes – proportions of students with:								
Any advanced course planned	0.53	0.65	0.56	N/A	0.58	0.61	0.51	N/A
At least one advanced ELA course planned	0.36	0.36	0.43	N/A	0.36	0.28	0.28	N/A
At least one advanced math course planned	0.40	0.56	0.47	N/A	0.48	0.52	0.39	N/A

Note. Sample includes eligible students in either T1 or T2. Any user click = a click on the alert by the focal student, their parent, or their counselor. N/A indicates never used course planner. Students did not receive an alert if their school did not offer a relevant advanced course or they had not completed prerequisites for available advanced courses, or if their school pre-populated an advanced course in the planner.

Table 6. Results of TOT Analyses Using Propensity Score Matched Samples

Outcome	T1 matched sample			T2 matched sample		
	T1 mean	C mean	T1-C	T2 mean	C mean	T2-C
Any advanced course			***n=692***			***n=1,058***
Planned Grade 10 any	0.49	0.51	-0.02	0.46	0.50	-0.03
Scheduled Grade 10 any	0.48	0.50	-0.02	0.44	0.47	-0.03
Rostered Grade 10 any	0.59	0.59	-0.00	0.67	0.60	0.06
Attempted Grade 10 any	0.49	0.50	-0.01	0.54	0.50	0.05
Passed Grade 10 any	0.48	0.49	-0.01	0.54	0.49	0.05
Planned Grade 11 any	0.65	0.28	0.37***	0.61	0.28	0.33***
Advanced ELA			***n=451***			***n=665***
Planned Grade 10 ELA	0.35	0.39	-0.04	0.34	0.43	-0.09
Scheduled Grade 10 ELA	0.35	0.39	-0.04	0.28	0.40	-0.12
Rostered Grade 10 ELA	0.33	0.39	-0.06	0.47	0.46	-0.01
Attempted Grade 10 ELA	0.34	0.38	-0.04	0.42	0.43	-0.01
Passed Grade 10 ELA	0.33	0.38	-0.05	0.42	0.43	-0.01
Planned Grade 11 ELA	0.35	0.24	0.11	0.37	0.18	0.19*
Advanced math			***n=440***			***n=791***
Planned Grade 10 math	0.40	0.37	0.03	0.35	0.39	-0.04
Scheduled Grade 10 math	0.37	0.36	0.01	0.32	0.37	-0.05
Rostered Grade 10 math	0.44	0.48	-0.04	0.54	0.45	0.10
Attempted Grade 10 math	0.36	0.36	0.00	0.46	0.39	0.07
Passed Grade 10 math	0.36	0.35	0.00	0.45	0.38	0.06
Planned Grade 11 math	0.50	0.20	0.29**	0.53	0.21	0.32***

Note. T1 = Treatment 1, T2 = Treatment 2, C = control. Matched samples were created separately for the T1-C comparisons and the T2-C comparisons. *p < .05, **p < .01, ***p < .001.

Figures

Figure 1. Theory of Action

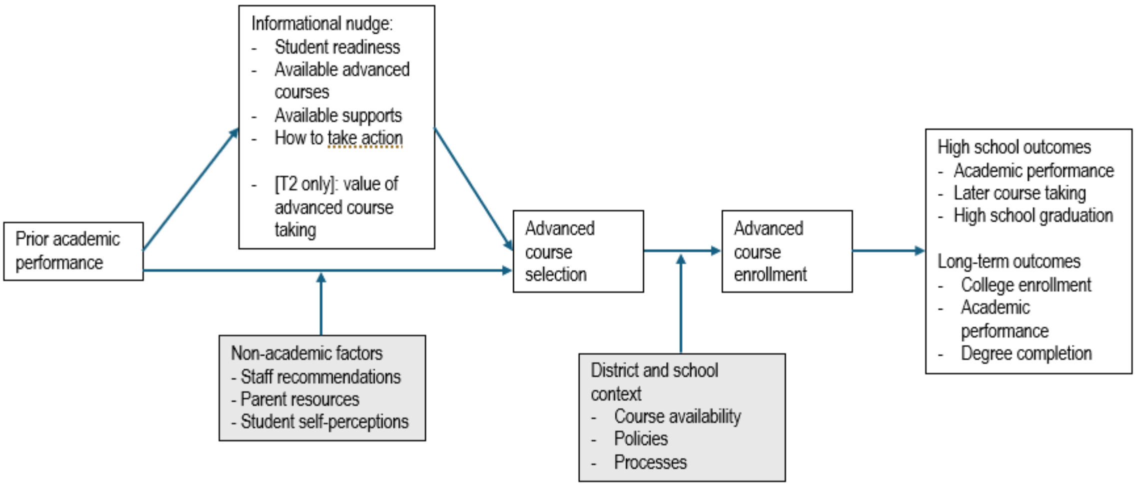
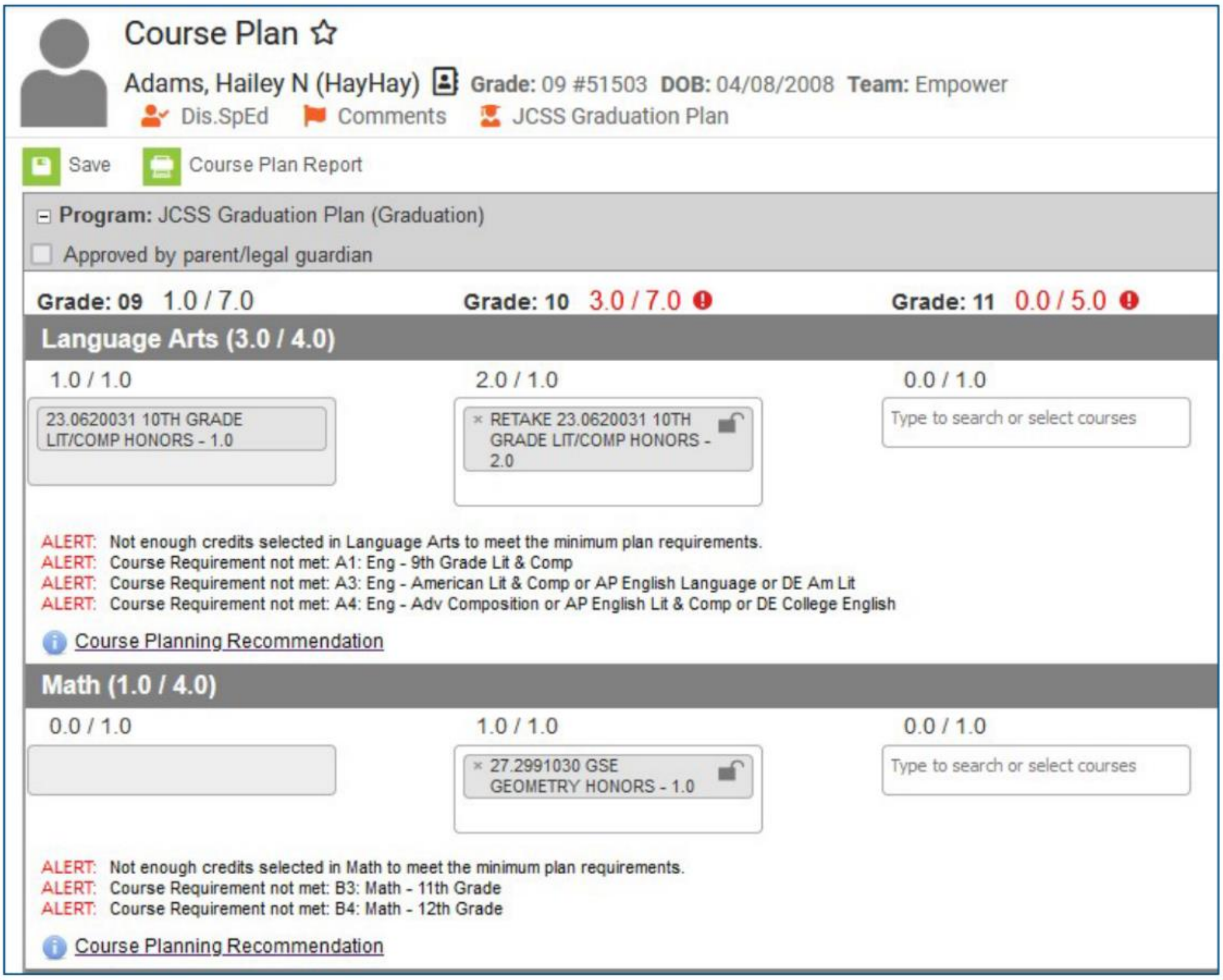


Figure 2. SIS Course Planner with Recommendation Icon and Link



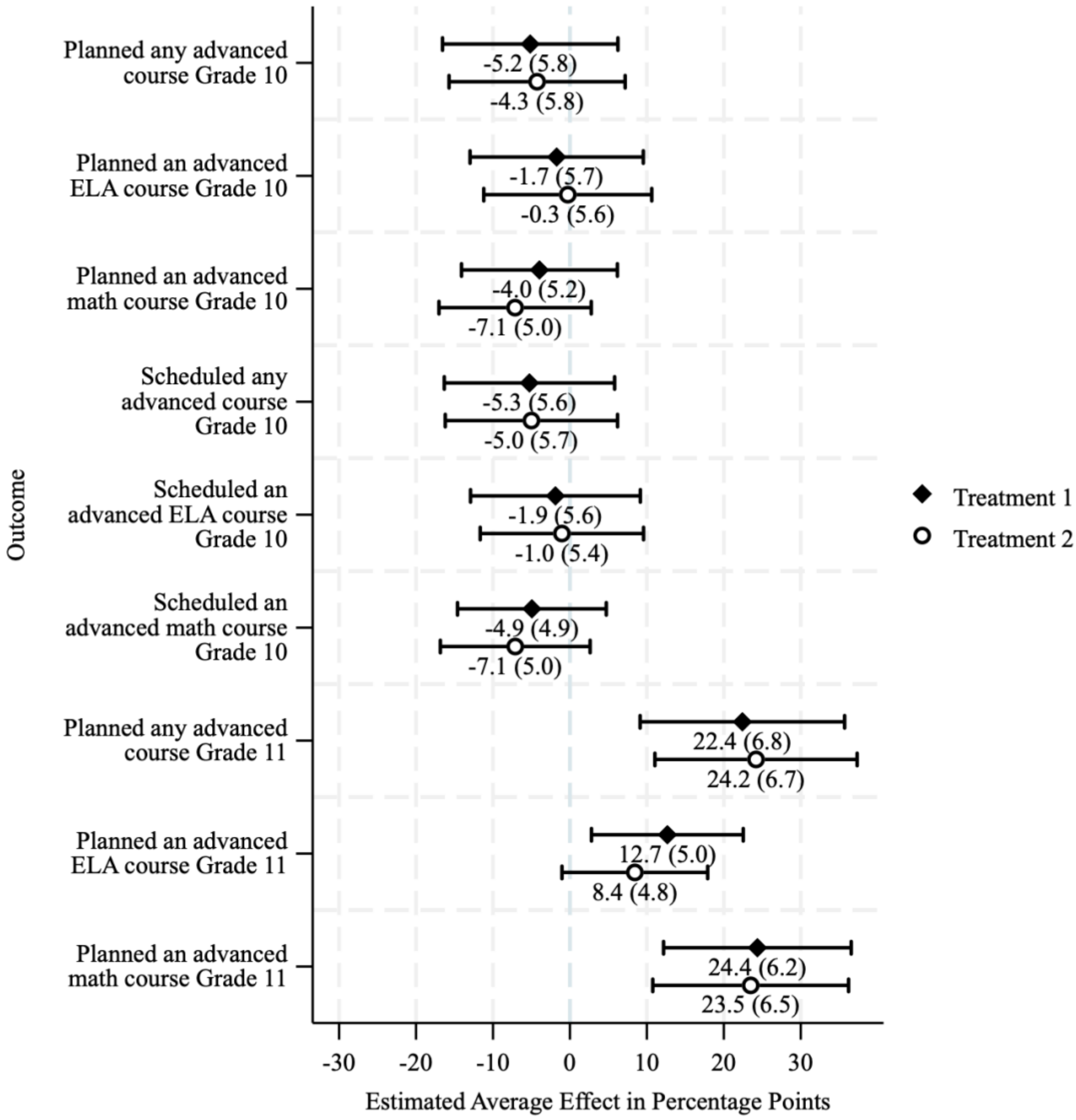
Note. Student information is fabricated. For each subject in which a student had a proficient test score or a prior grade of B- or higher, the student saw the blue "i" icon and "Course Planning Recommendation" alert. Clicking on the alert opened a pop-up that displayed the notification text.

Figure 3. Notification Text for Customized Course Recommendations

Treatment 1. Basic Information Only
[**Student first name**], your academic performance in **math** shows you have the ability to do well in advanced courses. Consider enrolling in an advanced **math** course next year, such as **[insert relevant courses here**]. Your parents/guardians, teachers, and counselors can help you learn more about this option and about supports available to help you succeed in an advanced course.
Treatment 2. Basic Information Plus Additional Information on AP Course Benefits
[**Student first name**], your academic performance in **math** shows you have the ability to do well in advanced courses. Consider enrolling in an advanced **math** course next year, such as **[insert relevant courses here**]. Taking advanced courses in high school can help you get into college, do well in college, and be ready for a career whether you plan to go to college or not. Your parents/guardians, teachers, and counselors can help you learn more about this option and about supports available to help you succeed in an advanced course.

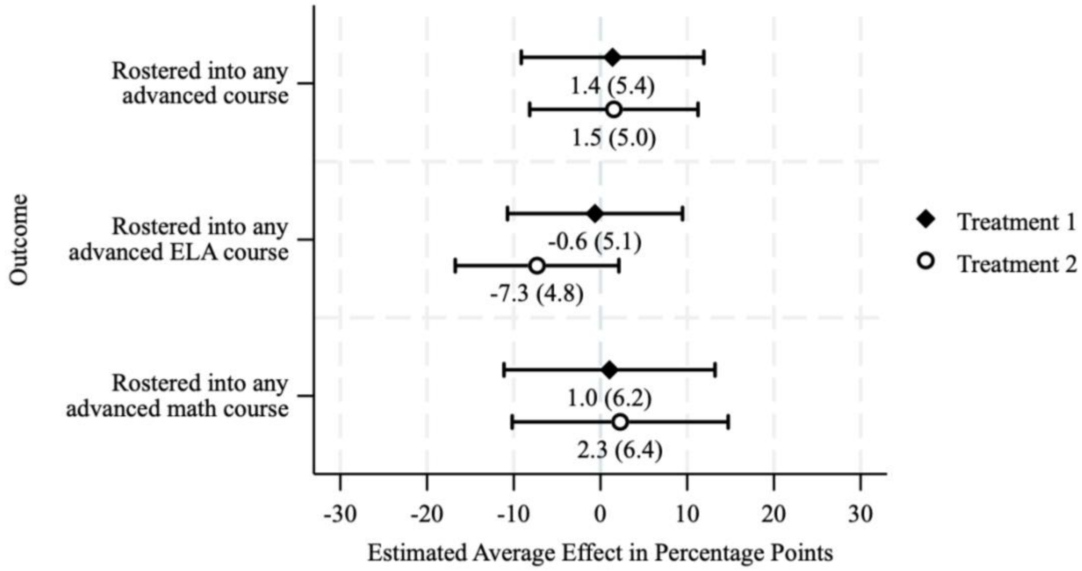
Note. Bolded text was customized to the student's name, subject for which they received the notification, and advanced courses offered in their school and for their grade level.

Figure 4. Intent-to-Treat Effects on Planning and Scheduling Advanced Courses in the Course Planner



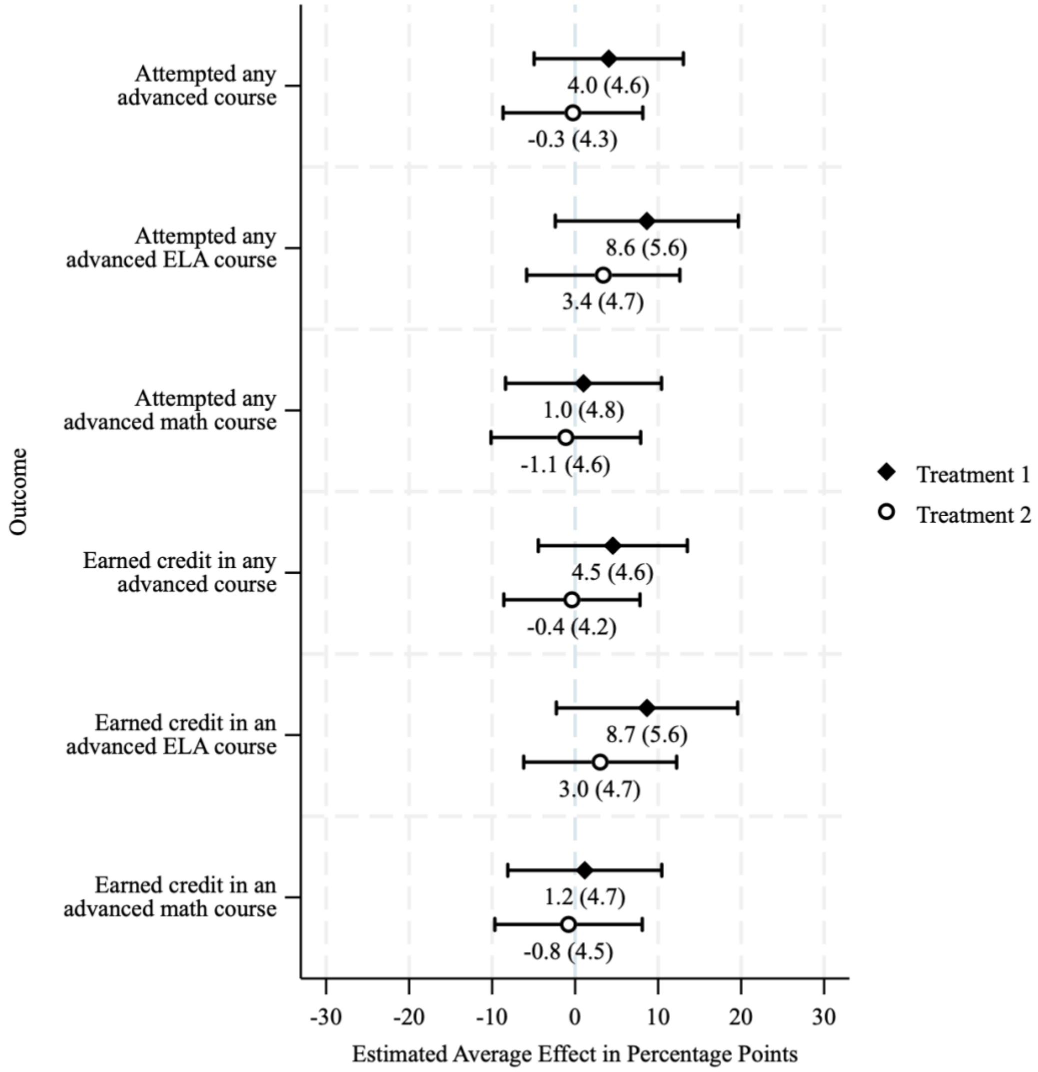
Note. Standard errors in parentheses.

Figure 5. Intent-to-Treat Effects on Rostering into Advanced Courses in Grade 10



Note. Standard errors in parentheses.

Figure 6. Intent-to-Treat Effects on Attempting and Earning Credit in Grade 10 Advanced Courses



Note. Standard errors in parentheses.

Appendix Materials

Propensity Score Matching Analytic Approach

To estimate treatment-on-the-treated (TOT) effects, we conducted propensity score matching (PSM) on a restricted sample of eligible students. We restricted the sample of students in each treatment condition to those who ever clicked on the alert to view the full notification text, and we restricted the comparison pool of students in the control condition to those who ever logged into the Course Planner. We then estimated the probability that a student clicked on the alert to view the notification text using the following equation:

$$P(Y_i = 1) = logit^{-1}(\alpha + \boldsymbol{\gamma} Student_i) \quad \text{(Eq. 3)}$$

The outcome, Y_i, indicates whether a student clicked on the alert to view the full notification; $Student_i$ is a vector of student-level characteristics including race/ethnicity, sex, EL status, special education status, and prior math and ELA course grades; and $\boldsymbol{\gamma}$ represents the associated coefficients. We estimated the model separately for T1 and control students and for T2 and control students. Using the estimated propensities, we matched students in the restricted sample in each treatment condition with students in the restricted sample in the control condition on their estimated propensity scores using 1:1 matching without replacement and a 0.2 standard deviation caliper. We then used the model in Equation 1 to analyze each binary outcome, respectively, using the matched analytic samples. We focused on the binary outcomes as there were no substantive or significant effects on the continuous outcomes.

Appendix Tables

Table A1. Proportion of Students Eligible for a Notification by Eligibility Pathway

Treatment 1 ELA (N=12,085)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.21**	**0.04**	**0.03**	**0.28**
	No	***0.15***	0.15	0.03	0.33
	Missing	***0.17***	0.10	0.13	0.40
	Total	***0.53***	0.29	0.19	

Treatment 1 Math (N=12,085)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.20**	**0.03**	**0.01**	**0.24**
	No	***0.15***	0.17	0.04	0.36
	Missing	***0.14***	0.13	0.13	0.40
	Total	***0.49***	0.33	0.18	

Treatment 2 ELA (N=12,307)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.16**	**0.03**	**0.04**	**0.23**
	No	***0.14***	0.14	0.04	0.32
	Missing	***0.22***	0.10	0.13	0.45
	Total	***0.52***	0.27	0.21	

Treatment 2 Math (N=12,307)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.14**	**0.02**	**0.01**	**0.17**
	No	***0.15***	0.18	0.04	0.37
	Missing	***0.21***	0.12	0.13	0.46
	Total	***0.50***	0.32	0.18	

Control ELA (N=13,469)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.22**	**0.04**	**0.04**	**0.30**
	No	***0.18***	0.18	0.04	0.40
	Missing	***0.11***	0.06	0.13	0.30
	Total	***0.51***	0.28	0.21	

Control Math (N=13,469)		***Eligible Course Grade***			
		Yes	No	Missing	Total
Eligible Assessment	Yes	**0.21**	**0.03**	**0.01**	**0.25**
	No	***0.18***	0.23	0.03	0.44
	Missing	***0.10***	0.07	0.13	0.30
	Total	***0.49***	0.33	0.17	

Note. Bold = First pathway to eligibility. **Bold/Italic** = Second pathway to eligibility. Total percentages may not sum to 100% due to rounding.

Table A2. Overall School and Student Attrition Rates

	Treatment 1	Treatment 2	Control	Overall
School				
Transcript	5.6%	5.4%	8.1%	6.4%
Roster	5.6%	5.4%	8.1%	6.4%
Event Log – Grade 10	5.6%	5.4%	8.1%	6.4%
Event Log – Grade 11	5.6%	5.4%	8.1%	6.4%
Student				
Transcript	12.2%	16.4%	18.2%	15.8%
Roster	12.0%	16.2%	18.0%	15.5%
Event Log – Grade 10	11.0%	15.3%	17.0%	14.6%
Event Log – Grade 11	11.5%	15.6%	17.4%	15.0%

Table A3. Differential School and Student Attrition Rates

	Treatment 1 vs. Control	Treatment 2 vs. Control	Treatment 1 vs. Treatment 2	Differential Attrition Threshold
School				
Transcript	2.6%	**2.7%**	0.2%	10.8%
Roster	2.6%	**2.7%**	0.2%	10.8%
Event Log – Grade 10	2.6%	**2.7%**	0.2%	10.8%
Event Log – Grade 11	2.6%	**2.7%**	0.2%	10.8%
Student				
Transcript	**6.0%**	1.8%	4.2%	10.9%
Roster	**6.0%**	1.8%	4.2%	10.6%
Event Log – Grade 10	**5.9%**	1.7%	4.2%	10.7%
Event Log – Grade 11	**5.9%**	1.8%	4.1%	10.7%

Note. The largest differential attrition for each outcome type is bolded. To be considered a low-attrition study, the maximum differential attrition must be below the differential attrition threshold for the optimistic boundary, which is listed in the right-hand column.

Table A4. Course Planner and Notification Tool Usage by Treatment Status, 2023-2024

	T1	T2	Control
Course Planner Logins			
Proportion of students with at least 1 student login	0.35	0.40	0.35
Average (Median) number of student logins	7.89 (4.0)	9.19 (4.0)	5.68 (5.0)
Proportion of students with at least 1 school staff login	0.68	0.62	0.58
Proportion of students with at least 1 parent login	0.10	0.13	0.07
Proportion of students with any user login	0.71	0.72	0.69
ELA Notifications			
Proportion of all eligible students identified as eligible for an ELA notification	0.89	0.88	0.88
Proportion of all eligible students sent an ELA notification during the 2023–24 school year	0.52	0.55	0.00
Of eligible students who were sent an ELA notification:			
Proportion of students who clicked on the notification	0.04	0.07	N/A
Proportion of students whose school staff clicked on the notification	0.01	0.02	N/A
Proportion of students whose parent(s) clicked on the notification	0.02	0.02	N/A
Proportion of students with any user view of the notification	0.06	0.10	N/A
Of users who viewed the ELA notification:			
Average (Median) seconds students spent viewing notification	18.2 (10)	13.64 (10)	N/A
Average (Median) seconds school staff spent viewing notification	8.62 (7.5)	27.29 (8)	N/A
Average (Median) seconds parents spent viewing notification	22.28 (15)	21.07 (16)	N/A
Average (Median) view length across all users in seconds	18.11 (11)	16.68 (10)	N/A
Math Notifications			
Proportion of all eligible students who were identified as eligible for a math notification	0.80	0.79	0.81
Proportion of all eligible students who were sent a math notification during the 2023–24 school year	0.50	0.52	0.00
Of students who were sent a math notification:			
Proportion of students who viewed the notification	0.04	0.08	N/A
Proportion of students whose school staff viewed the notification	0.01	0.02	N/A
Proportion of students whose parent(s) viewed the notification	0.01	0.02	N/A
Proportion of students with any user view of the notification	0.06	0.11	N/A
Of users who viewed the math notification:			
Average (Median) seconds students spent viewing notification	16.33 (10)	16.78 (10)	N/A
Average (Median) seconds school staff spent viewing notification	59.32 (9)	33.42 (7)	N/A
Average (Median) seconds parents spent viewing notification	28.44 (13)	19.8 (14)	N/A
Average (Median) view length across all users	21.56 (10)	18.74 (10)	N/A
Grade 10 Advanced Courses Planned			
Of students who were eligible for a notification:			
Proportion with at least one advanced ELA course planned	0.23	0.23	0.22
Proportion with at least one advanced math course planned	0.20	0.15	0.21
Average number of advanced courses planned	0.97	0.79	0.87
Proportion with at least one advanced ELA course scheduled	0.23	0.22	0.21

	T1	T2	Control
Proportion with at least one advanced math course scheduled	0.19	0.15	0.20
Average number of advanced courses scheduled	0.95	0.75	0.84
Proportion with at least one advanced ELA course rostered	0.36	0.30	0.31
Proportion with at least one advanced math course rostered	0.45	0.45	0.41
Average number of advanced courses rostered	1.32	1.12	1.21
Of students who were sent a notification:			
Proportion with at least one advanced ELA course planned	0.32	0.33	N/A
Proportion with at least one advanced math course planned	0.26	0.22	N/A
Average number of advanced courses planned	0.88	0.81	N/A
Proportion with at least one advanced ELA course scheduled	0.31	0.31	N/A
Proportion with at least one advanced math course scheduled	0.25	0.22	N/A
Average number of advanced courses scheduled	0.85	0.77	N/A
Proportion with at least one advanced ELA course rostered	0.36	0.36	N/A
Proportion with at least one advanced math course rostered	0.52	0.55	N/A
Average number of advanced courses rostered	1.32	1.37	N/A
Grade 11 Advanced Courses Planned			
Of students who were eligible for a notification:			
Proportion with at least one advanced ELA course planned	0.26	0.21	0.10
Proportion with at least one advanced math course planned	0.38	0.36	0.11
Average number of advanced courses planned	1.29	1.16	0.68
Of students who were sent a notification:			
Proportion with at least one advanced ELA course planned	0.36	0.29	N/A
Proportion with at least one advanced math course planned	0.55	0.52	N/A
Average number of advanced courses planned	1.24	1.18	N/A

Note. T1 = Treatment 1, T2 = Treatment 2, C = control, ELA = English Language Arts.

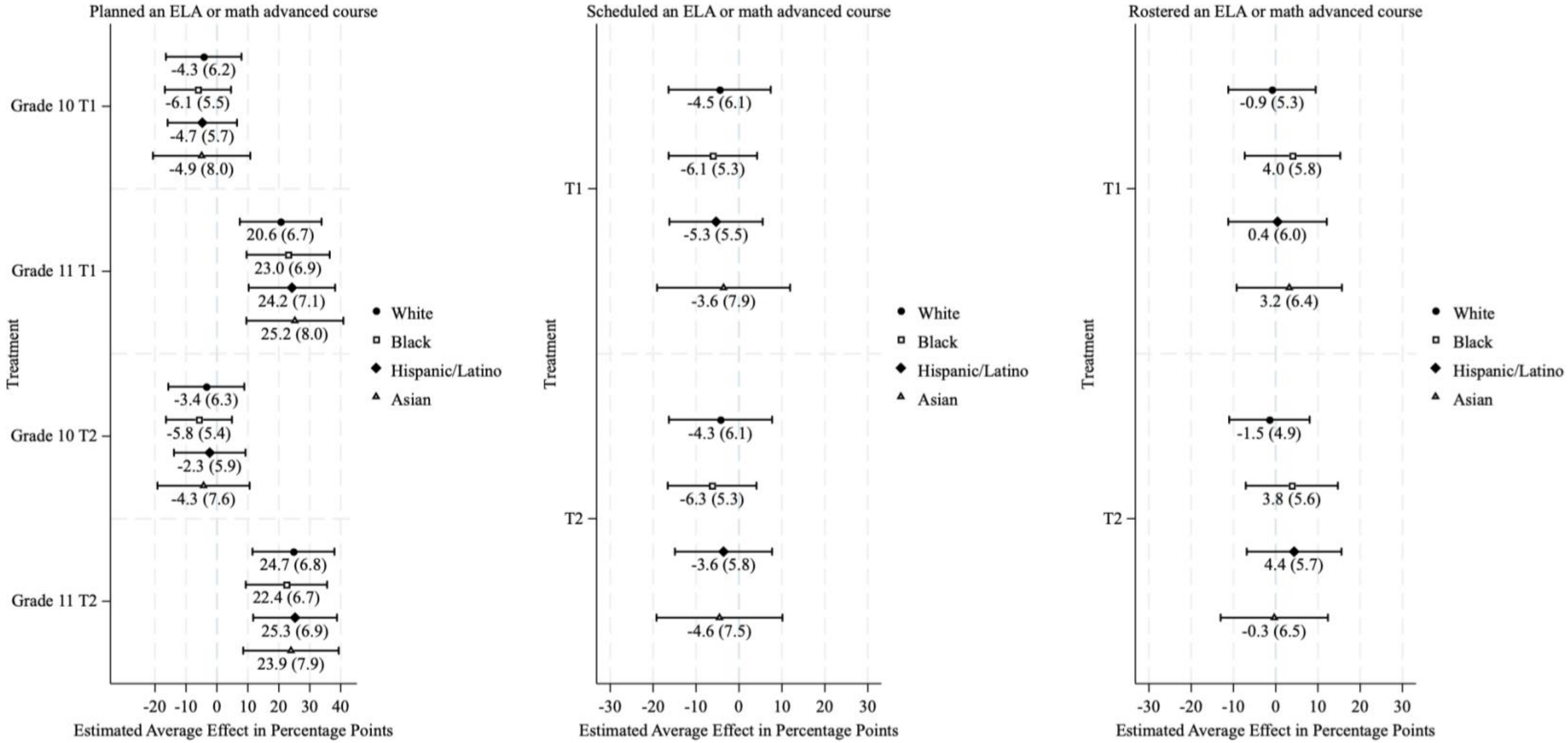
Table A5. Sample balance before and after propensity score matching

	Unmatched			Matched			Unmatched			Matched		
	T1	C	p-value	T1	C	p-value	T2	C	p-value	T2	C	p-value
Any advanced course												
Female	0.54	0.51	0.31	0.53	0.55	0.76	0.54	0.51	0.17	0.54	0.55	0.81
Hispanic	0.15	0.21	0.01	0.15	0.18	0.22	0.23	0.21	0.14	0.23	0.21	0.55
Black	0.25	0.29	0.06	0.25	0.24	0.66	0.19	0.29	0.00	0.19	0.20	0.82
Asian	0.05	0.03	0.16	0.04	0.03	0.56	0.06	0.03	0.00	0.06	0.06	1.00
Other race/ethnicity	0.04	0.06	0.09	0.04	0.04	0.85	0.07	0.06	0.25	0.07	0.08	0.72
ELA grade	1.93	0.36	0.00	2.10	2.43	0.59	1.49	-0.36	0.00	1.46	1.99	0.24
Math grade	1.19	-0.30	0.00	1.39	1.85	0.48	2.08	-0.30	0.00	2.08	2.14	0.89
Advanced ELA												
Female	0.52	0.53	1.00	0.52	0.53	0.93	0.53	0.53	0.95	0.53	0.53	0.88
Hispanic	0.14	0.19	0.07	0.15	0.15	1.00	0.19	0.19	0.98	0.19	0.17	0.43
Black	0.24	0.28	0.23	0.25	0.26	0.75	0.22	0.28	0.01	0.22	0.24	0.53
Asian	0.05	0.03	0.18	0.04	0.04	1.00	0.04	0.03	0.37	0.04	0.04	1.00
Other race/ethnicity	0.04	0.06	0.18	0.04	0.04	1.00	0.06	0.06	0.72	0.06	0.06	0.87
ELA grade	0.31	-0.16	0.34	0.27	0.95	0.33	1.12	-0.16	0.00	1.11	1.40	0.53
Math grade	0.14	-0.13	0.67	0.29	0.20	0.92	1.60	-0.13	0.00	1.64	1.83	0.74
Advanced math												
Female	0.57	0.51	0.12	0.56	0.57	0.85	0.55	0.51	0.11	0.55	0.56	0.89
Hispanic	0.15	0.19	0.20	0.15	0.16	0.80	0.24	0.19	0.02	0.24	0.25	0.62
Black	0.21	0.27	0.04	0.22	0.21	0.91	0.16	0.27	0.00	0.16	0.17	0.85
Asian	0.05	0.03	0.29	0.05	0.04	0.82	0.06	0.03	0.00	0.06	0.06	0.77
Other race/ethnicity	0.04	0.06	0.10	0.04	0.04	0.81	0.08	0.06	0.08	0.08	0.08	0.80
ELA grade	2.55	-0.26	0.00	2.55	2.61	0.95	1.21	-0.26	0.00	1.21	1.67	0.42
Math grade	0.91	-0.17	0.02	1.19	1.28	0.86	1.27	-0.17	0.00	1.25	1.36	0.77

Note. T1 = Treatment 1, T2 = Treatment 2, C = control, ELA = English Language Arts. ELA and math grades are grand-mean centered. Matched samples were created separately for the T1-C comparisons and the T2-C comparisons.

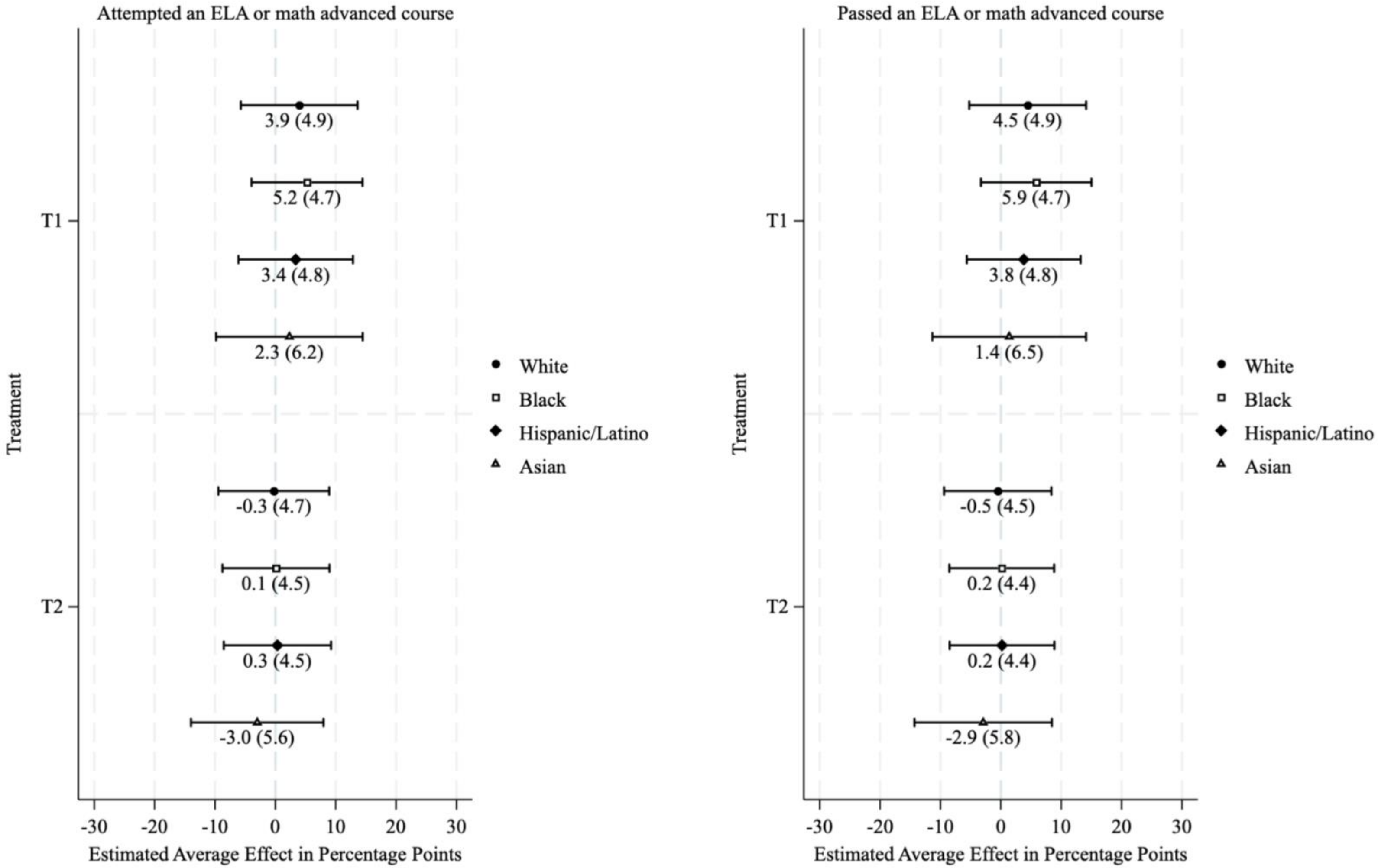
Appendix Figures

Figure A1. Effect Heterogeneity by Race/Ethnicity, Planning, Scheduling, and Rostering into Advanced Courses



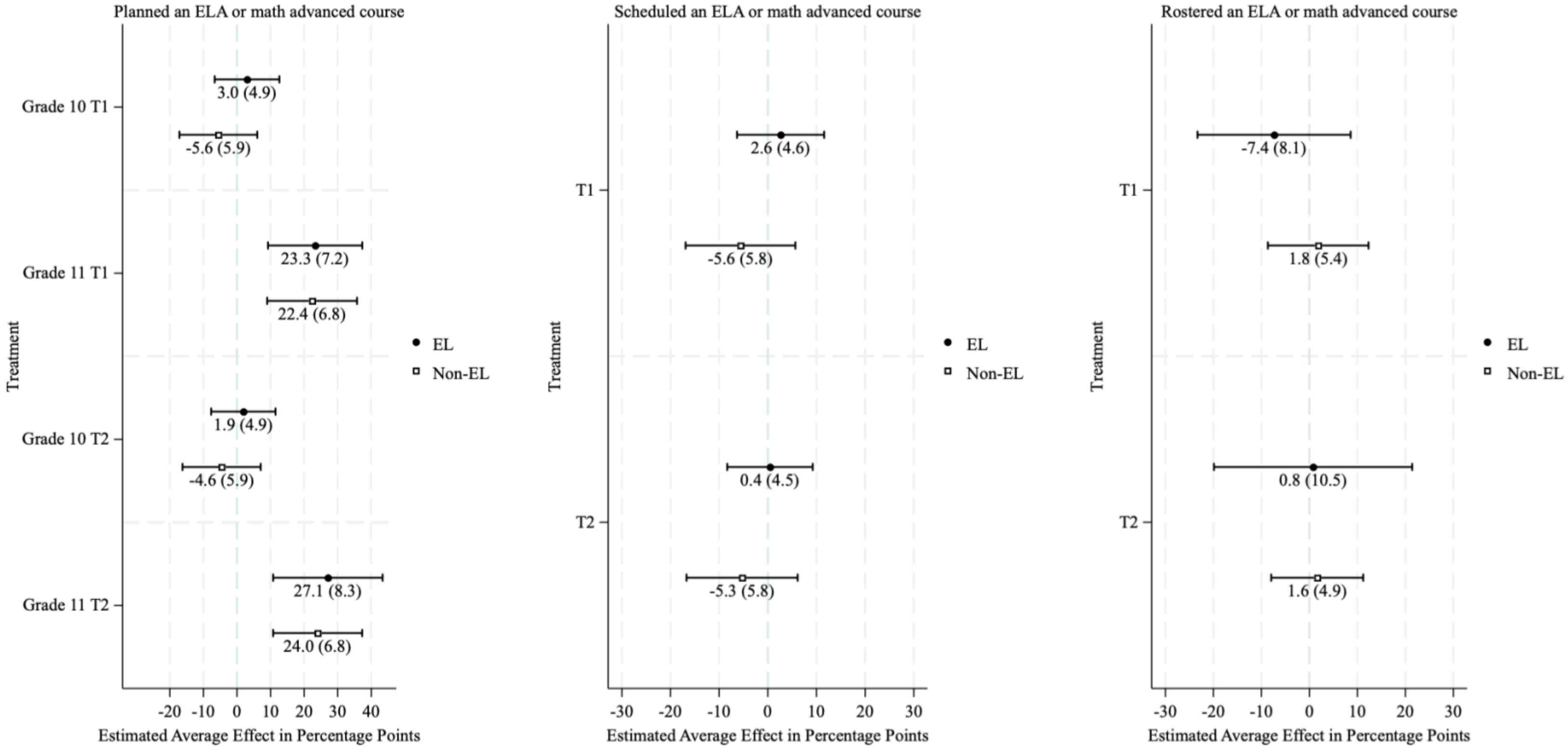
Note. Standard errors in parentheses.

Figure A2. Effect Heterogeneity by Race/Ethnicity, Attempting and Passing Advanced Grade 10 Courses



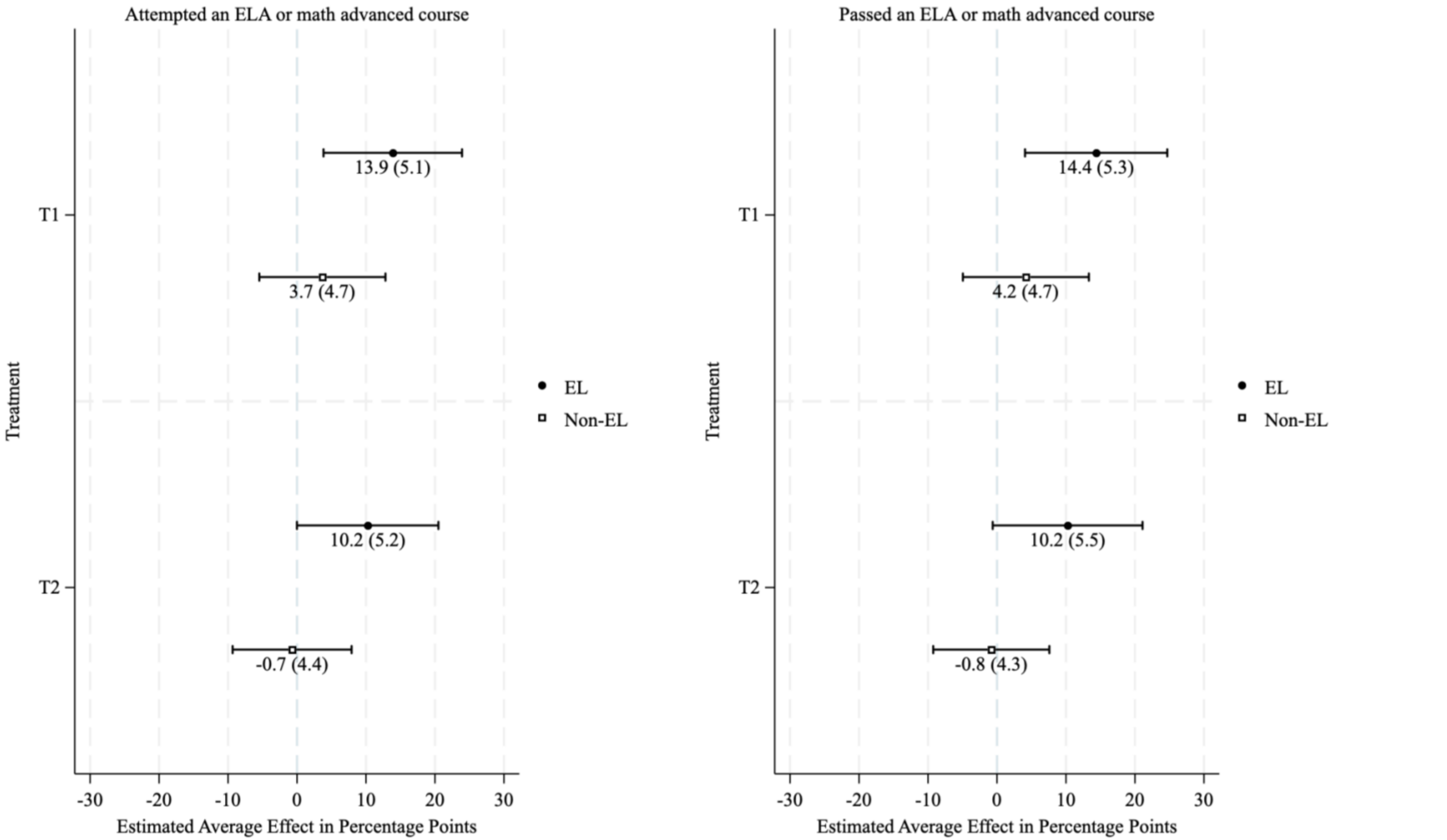
Note. Standard errors in parentheses.

Figure A3. Effect Heterogeneity by EL Status, Planning, Scheduling, and Rostering into Advanced Courses



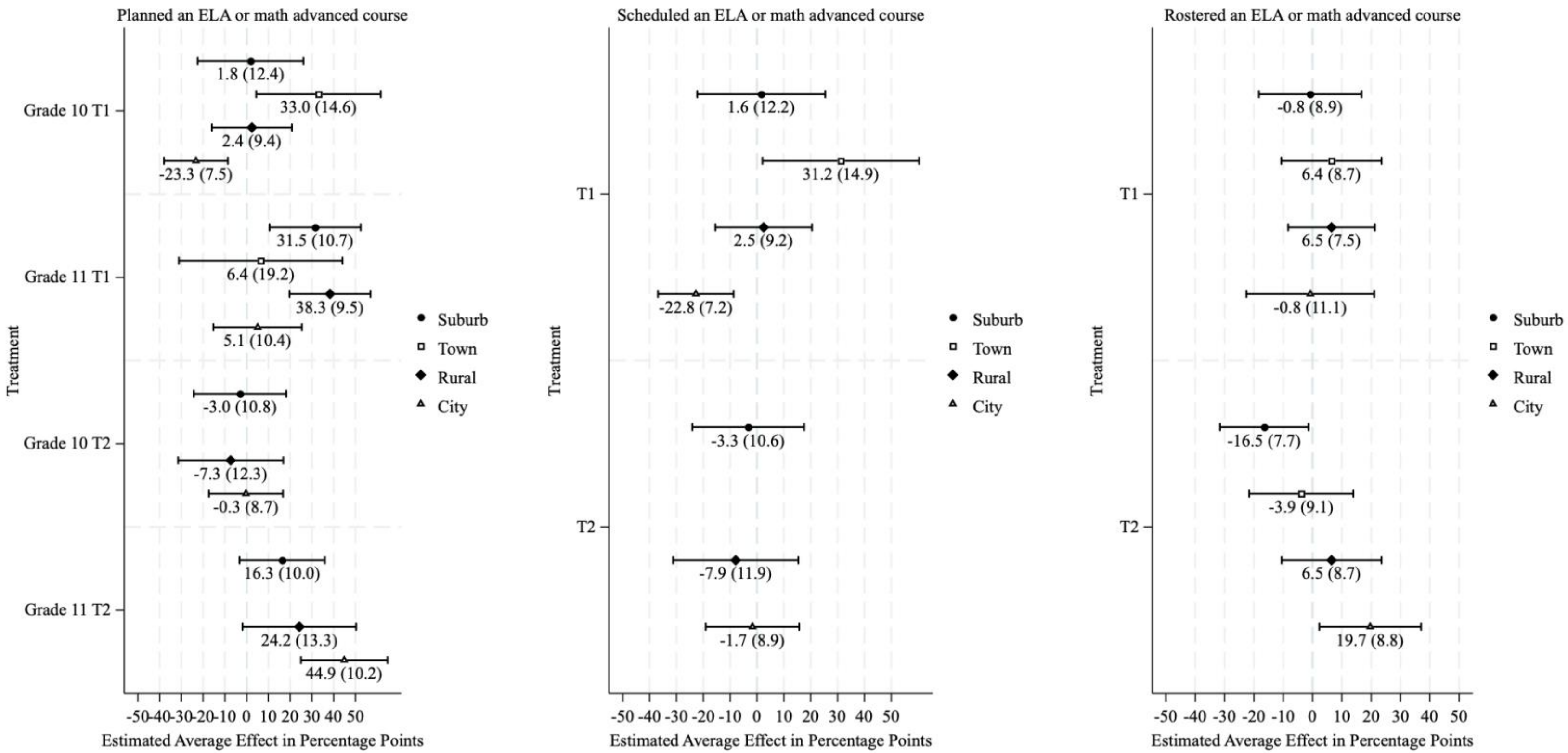
Note. Standard errors in parentheses.

Figure A4. Effect Heterogeneity by EL Status, Attempting and Passing Advanced Grade 10 Courses



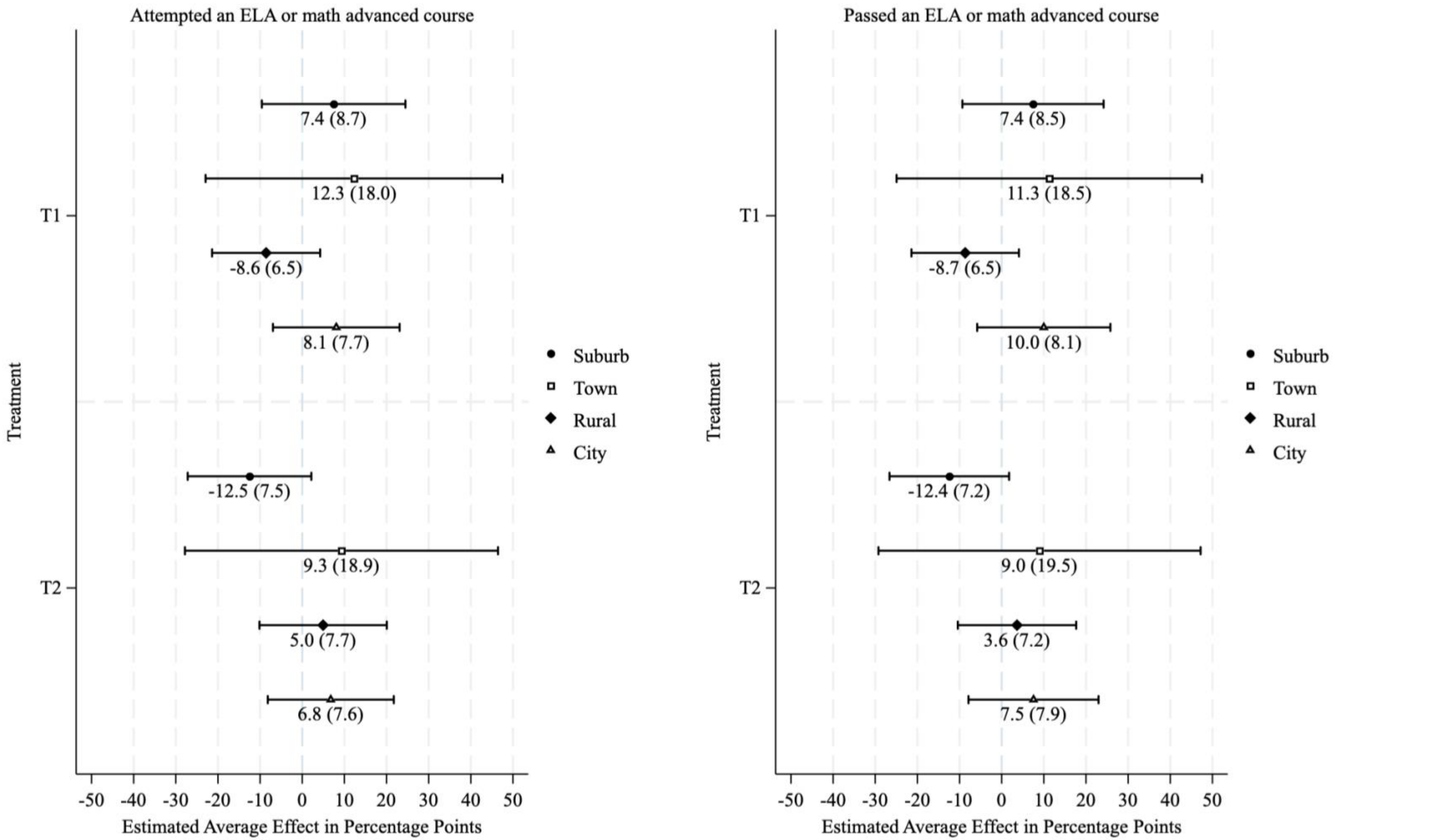
Note. Standard errors in parentheses.

Figure A5. Effect Heterogeneity by Locale, Planning, Scheduling, and Rostering into Advanced Courses



Note. Standard errors in parentheses.

Figure A6. Effect Heterogeneity by Locale, Attempting and Passing Advanced Grade 10 Courses



Note. Standard errors in parentheses.