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Advanced Math Course Taking: Effects on Math Achievement and College Enrollment

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Abstract

Using data from the Educational Longitudinal Study of 2002–2006 (ELS:02/06), this study investigated the effects of advanced math course taking on math achievement and college enrollment and how such effects varied by socioeconomic status (SES) and race/ethnicity. Results from propensity score matching and sensitivity analyses showed that advanced math course taking had positive effects on math achievement and college enrollment. Results also demonstrated that the effect of advanced math course taking on math achievement was greater for low SES students than for high SES students, but smaller for Black students than for White students. No interaction effects were found for college enrollment. Limitations, policy implications, and future research directions are discussed.

Keywords

Advanced math course taking; propensity score matching; SES; race/ethnicity

Mathematics is a gatekeeper for future educational and occupational opportunities, and it may be especially central to improving the economic and social conditions of youth especially from disadvantaged backgrounds (Meece, Eccles, Kaczala, Goff, & Futterman, 1982; Moses & Cobb, 2001; Sadler & Tai 2007; Schoenfeld, 2002). Consistent with the gatekeeper notion, literature highlights the importance of math course taking for college enrollment and selectivity (Adelman, 1999; Adelman, Daniel, & Berkovits, 2003; Schneider, 2003). Furthermore, prior research shows that advanced math course taking may positively affect several other educational outcomes including standardized test scores, high school completion, college performance, and postsecondary degree completion (Adelman, 2006; Attewell & Domina, 2008; Long, Iatarola, & Conger, 2009; Schneider, 2003; Schneider, Swanson, & Riegle-Crumb, 1998; Stevenson, Schiller, & Schneider, 1994). Economists have also shown that advanced math course taking in high school may impact earnings in adulthood and more so than other subjects (Altonji, 1995; Joensen & Nielsen, 2009; Levine & Zimmerman, 1995; Rose & Betts, 2004).

Yet, prior research on math course taking has two important limitations. One problem apparent in the literature is that it is largely unclear whether advanced math course taking has a causal effect on outcomes (Joensen & Nielsen, 2009; Long, Conger, & Iatarola, 2012). The crux of the problem is that students who take advanced courses systematically differ from those who do not (Attewell & Domina, 2008; Lee & Ready, 2009). For example, substantial evidence indicates that high-achieving students from high socioeconomic status (SES) families are more likely to take advanced courses (Kelly, 2009; Long et al., 2009; Riegle-Crumb & Grodsky, 2010; Schneider et al., 1998; Sciarra, 2010). These preexisting differences can produce selection effects that make it difficult to identify a causal link between advanced course taking and educational outcomes. Most prior research has used regression analyses with the inclusion of control variables (e.g., ACT, 2005; Gamoran & Hannigan, 2000; Lee, Chow-Hoy, Burkam, Geverdt, & Smerdon, 1998; Schneider et al., 1998; Sebring, 1987), but literature suggests that this conventional regression method is often not effective to reducing selection bias (Morgan & Winship, 2007; Rosenbaum & Rubin, 1983; Schneider, Carnoy, Kilpatrick, Schmidt, & Shavelson, 2007).

A second problem in the literature is that most research focuses on the average effect of advanced math course taking. An underlying assumption of this research is that all students should receive similar benefits from taking advanced math courses, regardless of their socioeconomic and racial/ethnic backgrounds. However, literature documents that there are substantial disparities in advanced math course taking among youth from low income and minority backgrounds (Dalton, Ingels, Downing, & Bozick, 2007; Ingels & Dalton, 2008). Furthermore, a main concern of policymakers and numerous others has been to improve access to advanced courses for youth from racial/ethnic minority and low SES backgrounds (Geiser & Santelices, 2004; Lee & Ready, 2009; Santoli, 2002). These concerns and efforts to improve access are based on a similar assumption that taking advanced math courses will improve the educational outcomes for youth from racial/ethnic minority and low SES backgrounds. Yet, little research has examined whether the effects of advanced course taking vary by SES and racial/ethnic backgrounds.

The current study builds on and extends prior research on taking advanced math courses by addressing these two problems. Specifically, to more rigorously investigate the effects of advanced math course taking on educational outcomes, we use longitudinal data for a nationally representative sample of high school students (i.e., Education Longitudinal Study of 2002–2006 [ELS:02/06]) and a series of statistical methods including propensity score matching (PSM). While other statistical methods can address selection bias (Schneider et al., 2007), PSM has been widely used in recent educational policy research (e.g., Callahan, Wilkinson, & Muller, 2010; Domina, 2009; Melguizo, 2010). In addition, we examine potential heterogeneity in the effects of advanced math course taking by SES and race/ethnicity. Identifying differential effects of advanced math course taking by SES and race/ethnicity is important because results can better inform policy makers as to whether advanced math course taking can help improve (or widen) the achievement gap among students of diverse backgrounds. In sum, the current study seeks to extend our knowledge about the role of advanced math course taking.

Literature Review

Effects of Advanced Math Course Taking

Advanced math course taking reflects a key educational experience, the math curriculum (Schneider et al., 1998; Wang & Goldschmidt, 2003). Advanced math course taking may impact important outcomes such as math achievement because advanced math course taking reflects the highest level of math completed (Burkam & Lee, 2003). When students have completed more advanced math courses, they have had the opportunity to learn additional math concepts and principles as well as sufficiently mastered lower level course content to take advanced courses (Dalton et al., 2007). Therefore, completing advanced math courses should enhance performance on math achievement tests. Advanced math course taking may also increase test scores beyond, for example, motivation and aspirations. This is because if students are more motivated or have high aspirations but for some reason they do not complete advanced math (e.g., not offered at their school) then they will have not been exposed to the more advanced math content (Wang & Goldschmidt, 1999).

Advanced math course taking may also affect college enrollment (Adelman, 1999, 2006; Adelman et al., 2003; Geiser & Santelices, 2004; Schneider, 2003). This is because while admissions decisions focus on overall GPA and performance on college entrance exams (e.g., ACT, SAT), another crucial factor is the number and level of high school courses taken (Riegle-Crumb & Grodsky, 2010). Moreover, college admission criteria often require completion of more and a higher level of courses in math than other subjects, with additional advanced math courses necessary for entrance into many programs (e.g., STEM fields) and postsecondary institutions (e.g., 4-year vs. 2-year college, selective universities). A focus on course taking is also consistent with educational policies and efforts that, as a necessary first step, have focused on reducing the inequitable access to advanced courses evident among youth from racial/ethnic minority and low SES backgrounds (Geiser & Santelices, 2004; Lee & Ready, 2009; Santoli, 2002). Indeed, studies suggest that inequities in access to and taking of advanced math are central to differences in the educational attainment (e.g., achievement, college enrollment) of youth from racial/ethnic minority, low SES, and English Language Learner backgrounds (Adelman, 1999; Kelly, 2009; Lee & Bryk, 1988; Riegle-Crumb & Grodsky, 2010; Wang & Goldschmidt, 1999, 2003).

Earlier studies that examined the effects of advanced course taking generally found strong, positive effects on educational outcomes. For example, Stevenson et al. (1994) found a strong positive relation of advanced math course taking on student outcomes (e.g., math test scores, college entry) even after controlling for family background and prior achievement. Several other studies reported similar results (Gamoran & Hannigan, 2000; Lee et al., 1998; Schneider et al., 1998; Sebring, 1987). Yet, these earlier studies used multivariate regression models to estimate the effect of advanced math course taking. Furthermore, these studies included a limited number of variables for background characteristics. For example, Sebring (1987) only considered aptitude while other studies included gender, parent education, and racial/ethnic background (e.g., Gamoran & Hannigan, 2000; Stevenson et al., 1994).

The use of multivariate regression models with a narrow set of variables, however, can lead to inappropriate causal inferences about the treatment effect (Rosenbaum & Rubin, 1983,

1985). That is, without accounting for the full array of covariates that may be involved in the process that leads students to being self-selected into taking advanced courses, the results from these earlier studies could be biased. Indeed, there is substantial evidence that several other important factors within the family (e.g., family composition, parental educational expectations, parental contact with or involvement in school), students' experiences outside and inside school (e.g., employment, time spent on homework, teacher expectations), and school characteristics (e.g., student body characteristics, school sector, geographic location) may affect advanced math course taking and educational attainment (Bozick & Ingels, 2008; Iatarola, Conger, & Long, 2011; Leow, Marcus, Zanutto, & Boruch, 2004; Kelly, 2009; Riegle-Crumb & Grodsky, 2010; Rose & Betts, 2004; Schneider et al, 1998; Sciarra, 2010).

A few recent studies have begun to use more rigorous methods to estimate the causal effects of advanced course taking. For example, Attewell and Domina (2008) conducted PSM analyses to estimate the effects of taking more advanced courses in data from the National Education Longitudinal Study of 1988–2000. Attewell and Domina (2008) used a broad measure of curricular intensity that captured the level of high school courses taken across several subjects rather than focusing on a single subject such as advanced math course taking. Nonetheless, results were informative because estimates revealed positive effects of a more intense curriculum on math achievement, college entry, and college completion.

Leow and colleagues (2004) also used PSM to estimate the causal effect of advanced math course taking on math achievement with 1995 data from the Trends in International Mathematics and Science Study (TIMSS). Leow et al. (2004) provided an important contribution by demonstrating that there was a positive effect of advanced math course taking on math achievement. However, their study is limited in that, as the authors acknowledged, the TIMSS data were cross-sectional and did not contain prior achievement, which is one of the important predictors of academic achievement and advanced-course taking (Gamoran & Hannigan, 2000; Schneider et al., 1998). Examining longitudinal effects would provide stronger evidence for the benefits of advanced math course taking.

In a recent study of high school course taking in Florida, Long et al. (2012) also used PSM and found that taking advanced math courses had a positive effect on math achievement and college enrollment. Studying students in a single state provided Long et al. (2012) unique benefits including data from students that were all subject to the same educational policies and graduation requirements. However, Florida is also distinct in several respects. Florida is a national leader in efforts to expand student participation in advanced courses (Dougherty, Mellor, & Jian, 2006; Iatarola et al., 2011). Florida's efforts have included professional development for teaching advanced courses in high needs schools and financial incentives for students taking and passing exams in advanced courses. Consequently, Florida had significant increases in advanced course offerings during the last decade. Florida also has numerous STEM-related job opportunities that provide students motivation for completing STEM courses and degrees (Tyson, Lee, Borman, & Hanson, 2007). As a consequence of these unique circumstances in Florida, the findings by Long et al. (2012) could have limited generalizability. In this study, we use nationally representative data which can better inform federal policy than state-specific data (McFarland, 2006).

SES and Racial/Ethnic Differences in the Effects of Advanced Course Taking

Numerous policies and efforts at federal, state, and local levels seek to enhance equitable access to advanced courses for youth from racial/ethnic minority and low SES backgrounds (Geiser & Santelices, 2004; Lee & Ready, 2009; Santoli, 2002). Yet, there are substantial disparities in advanced math course taking among youth from low income and minority backgrounds (Dalton et al., 2007; Ingels & Dalton, 2008). With respect to the racial/ethnic gap in advanced math course taking, for example, the proportions of students taking precalculus were 14% and 15% for African American and Hispanic/Latino(a) youth in 2004, whereas the corresponding proportion was 21% for White students (Dalton et al. 2007; Ingels & Dalton, 2008).

Although limited, recent research has begun to examine whether the effects of advanced course taking may vary for youth from different backgrounds; findings have been mixed. Attewell and Domina (2008) found that the estimated causal effect of their more general measure of curricular intensity on 12th grade math achievement was significantly larger for African American students than White students. However, the effects of curricular intensity on math achievement, college enrollment, and degree completion did not vary by the composition of schools (i.e., percentage of students from various racial/ethnic and economic backgrounds). Among students in Florida, compared to white, middle class students, Long et al. (2012) found no differences in the effects of advanced math course taking on math achievement for youth from high poverty and minority backgrounds. Nonetheless, there was a stronger effect on enrollment in a 2-year college for youth from high poverty, African American, and Hispanic backgrounds but a weaker effect on enrollment in a 4-year college for youth from high poverty backgrounds.

Some research using other analytic approaches has also suggested that there may be racial/ethnic variation in the effects of advanced math course taking. Long et al. (2009) used probit regression and demonstrated that African American and Asian students obtained smaller benefits from advanced math course taking on math college readiness at all levels of math course taking than White students. In addition, Hispanic students received more benefit in math college readiness from taking precalculus or higher, less benefit from taking Algebra 2, and comparable benefit from other math courses while students from high poverty backgrounds received a smaller benefit at all levels of course taking than White students. Correlational data from Florida have revealed no racial/ethnic differences in the relationship of math course taking to math achievement (Roth, Crans, Carter, Ariet, & Resnick, 2000–2001). In contrast, findings from Texas have indicated that youth from African American, Hispanic, and low income backgrounds obtain less benefit for achievement (Dougherty et al., 2006). In sum, the limited work and mixed findings on variation in the effects of advanced course taking by students' racial/ethnic and SES background signify that more research is needed.

Data and Method

Data

Data were from the restricted use version of the ELS:02/06 conducted by the National Center for Education Statistics (NCES). ELS:02/06 first collected data from a nationally representative sample of U.S. high school sophomores in the spring of 2002 and consisted of approximately 16,000 participants. Data were then obtained two years later when most participants were seniors (spring of 2004) and four years later when most participants were two years out of high school (spring of 2006). We restricted our analytic sample to students who participated in the base year survey, both follow-up surveys, and had complete high school transcript information. We excluded students from Native American backgrounds due to small sample size. The final analytic sample involved 12,250 participants (statistical standards for restricted-use data require that unweighted sample sizes be rounded to the nearest 10). For multivariate analyses, we applied the longitudinal base year to second follow-up panel weight (F2BYWT).

Measures

Advanced math course taking—Advanced math course taking was captured using the mathematics pipeline measure developed by Burkam and Lee (2003). In the current study, the mathematics pipeline measure in the ELS:02/06 data reflects the content of students' course taking across high school (Dalton et al., 2007). We constructed a dichotomous measure of the advanced level of math that students reached during high school. Advanced math course taking was operationalized by having completed at least one course beyond algebra 2, including trigonometry, precalculus, and calculus. Though this is perhaps an overly simplistic measure of advanced math course taking, this operationalization is based on findings indicating that taking at least one math course beyond algebra 2 has the strongest relation to secondary achievement and postsecondary enrollment and success (ACT, 2005; Adelman, 1999). This operationalization is also consistent with prior research (e.g., Riegle-Crumb & Grodsky, 2010). In the analytic sample, 6,020 students (51%) were advanced math course takers.

The pipeline measure draws on the Classification Scheme of Secondary School Courses (CSSC). The NCES developed the CSSC through extensive efforts to provide a common classification system for all secondary school courses in the U.S. (Burkam & Lee, 2003; Dalton et al., 2007). The CSSC provides a standardized record and ensures comparability of the courses taken by students for a variety of key stakeholders and uses including school districts (e.g., student moves to new school), postsecondary institutions (e.g., admissions decisions), and research (Bradby, Pedroso, & Rogers, 2007). The CSSC has detailed definitions for the content of each course such that a course identified as, for example, algebra 2 has content that NCES deemed equivalent (for more details, see Bradby et al., 2007; Burkam & Lee, 2003; Dalton et al., 2007).

Educational outcomes—The outcomes capturing secondary and postsecondary educational achievement were (a) mathematics achievement in the 12th grade, (b) college enrollment status, and (c) type of college enrollment. Mathematics achievement was

measured by a standardized test administered during first follow-up (spring of 2004) when most participants were in the 12th grade, and scaled with a mean of 50 and standard deviation of 10. The variable was a continuous measure of the number of items the student would have answered correctly had he/she taken the entire mathematics test and was based on IRT scaled math achievement test scores. ELS:02/06 math assessment was a two-stage test. In 10th grade, all students received a short multiple-choice routing test and depending on the number of correct answers each student was assigned to a low, middle, or high difficulty second-stage form. For the 12th grade testing, students were then assigned to an appropriate test form based on their performance in 10th grade (for more details see Ingels et al., 2007). College enrollment status was measured by whether the student was ever enrolled in a postsecondary institution (including a 2- and 4-year program) as of 2006. We also examined the types of college in which the student was enrolled (2-year college enrollment vs. 4-year college enrollment vs. no college enrollment).

In the full sample, the average math achievement score was 148.83 and 72% were enrolled in college (27% in 2-year college and 45% in 4-year college, Table 1). There were differences in math achievement and college enrollment between students who took advanced math courses and students who did not. For example, 73% of students who took advanced math courses enrolled in a 4-year college, but only 22% of students who did not take advanced math courses enrolled in a 4-year college.

Covariates—Based on prior research, we carefully selected both student- and school-level covariates that might affect both advanced math course taking and educational outcomes. These covariate variables were taken from the data collected in the 10th grade and included several measures at the student- and school-level. The inclusion of a more comprehensive set of covariates is significant because, as mentioned, previous studies have included a limited number of control measures and these largely only involved student-level background characteristics (e.g., Gamoran & Hannigan, 2000; Sebring, 1987; Stevenson et al., 1994). For the student-level covariates, we included (a) SES, (b) family structure, (c) number of siblings, (d) parental educational expectations, (e) parent-child discussion, (f) parent contact school, (g) parent-parent interaction, (h) race/ethnicity, (i) gender, (j) student educational expectations, (k) ever in an ESL program, (l) previous math achievement, (m) previous reading achievement, (n) 10th grade cumulative GPA, (o) worked part-time, (p) in a general vs. college prep vs. vocational track, (q) teacher's education expectations, and (r) student motivation and engagement. For the school-level covariates, we included (s) % of free lunch, (t) % of minority students, (u) school sector, and (v) urbanicity. Detailed descriptions of these variables are provided in Appendix A and B.

Analytic Strategies

In the current study, we used PSM as a data preprocessing technique in order to estimate the causal effects of advanced math course taking as well as to examine variation in the effects of advanced math course taking by SES and race/ethnicity. Specifically, first, using the full unmatched sample, we completed preliminary descriptive analyses. Depending on the measure's scale, we conducted univariate linear, logistic, or multinomial regression for each covariate to determine if there were preexisting differences between students who took

advanced math courses and those who did not. We then performed a logistic regression analysis with all covariates predicting advanced math course taking to examine adjusted differences in background characteristics between students who took advanced math courses and those who did not.

Next, we examined the effect of advanced math course taking in the unmatched sample. Specifically, we conducted (a) ordinary least squares (OLS) regression for math achievement, (b) logistic regression for college enrollment status, and (c) multinomial regression for the type of college enrollment, respectively, depending on the scale of the outcome variables. To more systemically investigate the effect of advanced math course taking, we estimated three models within each regression analysis. The first model included advanced math course taking only. The second model added the covariates and the aim was to examine whether the effect of advanced math course taking held after controlling for the covariates. The third model included the interaction of SES and race/ethnicity with advanced math course taking and the aim was to examine variation in the effects of advanced math course taking by SES and race/ethnicity.

We then estimated the effects of advanced math course taking by employing a PSM approach as data preprocessing via the following. First, we conducted a logistic regression to generate propensity scores from the covariates. This entailed regressing the covariates on the dichotomous measure of advanced math course taking to obtain the predicted probability (i.e., propensity score) of taking advanced math. Second, we used the propensity scores to match treated (i.e., students who took advanced math courses) and control participants (i.e., students who did not) through the *psmatch2* module in Stata. Participants were matched one-to-one (i.e., one control participant for each treated participant) by the nearest neighbor within a caliper matching method (Rosenbaum & Rubin, 1985).¹ This method selects the control participant that is the best match (i.e., nearest neighbor) for a treated participant among the control participants that are within the absolute distance of the propensity scores between the prespecified tolerance or range for the size of the caliper. Following Rosenbaum and Rubin's (1985) recommendation, we used a .25 standard deviation of the estimated propensity score as the caliper size.² Third, we then replicated the OLS, logistic, and multinomial regression analyses described above with the matched sample. It is important to note that we included all covariates used to generate propensity scores when running these regression models on the matched samples because combining matching methods with regression yield less biased estimates effects than does either method alone (Stuart, 2007). Finally, we performed sensitivity analyses using the Rosenbaum bounds approach to evaluate the extent to which estimated effects were sensitive to unobserved variables (see Rosenbaum, 2002; see also Becker & Caliendo, 2007; DiPrete & Gangl,

¹We chose the one-to-one nearest neighbor matching approach over other PSM methods (e.g., stratification, inverse weights) because we believed this approach would be more straightforward than other methods to understand the results for the matched and unmatched samples, as we used the same regression-type analysis for these two different samples. In addition, in our study, we were interested in estimating not only the average effect but also the heterogeneous effect across specific demographic groups of students in terms of SES and race/ethnicity. However, with stratification, we can examine the heterogeneous treatment effects only across different strata, but not across specific demographic groups, because with stratification by the propensity score, the average effect is calculated with each stratum and then averaged across strata. Meanwhile, we did not use inverse probability weighting because a more sophisticated sensitivity analysis using the Rosenbaum bounds approach in Stata is currently unavailable.

²We replicated propensity score analyses with different caliper sizes and found few differences the findings reported in this study. The results from propensity score analyses with different caliper sizes are available upon request from the authors.

2004). This method assesses how strongly unmeasured confounding variables may affect selection into treatment and undermine the conclusions about causal effects (DiPrete & Gangl, 2004). Sensitivity analyses using the Rosenbaum bounds method are currently possible only for continuous and binary measures (*rbounds* and *mbounds* commands, respectively) in Stata (Becker & Caliendo, 2007; DiPrete & Gangl, 2004). Therefore, we conducted sensitivity analyses for math achievement and college enrollment status but not for the type of college enrollment.

We replaced missing data for the covariates using multiple imputations (Schafer & Graham, 2002) (see Appendix A for the percentage of missing data for the covariates).³ Following the recommendations (von Hippel, 2007), we included all of the dependent variables and covariates so that missing values for the covariates were predicted using existing values from the other variables. Given literature suggesting that accurate results typically can be obtained from two to ten imputations (von Hippel, 2005; Rubin, 1987), we generated five imputed data sets, conducted regression analyses with each imputed data set before and after matching, and then averaged the coefficients and standard errors by using Rubin's (1987) rule. To address the nested nature of the data (i.e., students were randomly selected within sampled schools), we used cluster robust standard errors, which downwardly adjust for the inflated standard errors resulting from the violation of the independent errors assumption and thus reduce the likelihood for type I error (Rogers, 1993).

Results

Preliminary Results

The weighted descriptive statistics in Table 1 showed significant differences in almost all preexisting observed covariates between students who took advanced math courses and students who did not. Logistic regression estimates also demonstrated that several of these covariates uniquely predicted advanced math course taking (Table 2). These results indicated that there was a selection issue in estimating the effects of advanced math course taking on educational achievement. Thus, using PSM to match control and treated participants seemed warranted and was undertaken.

Note that the sample size for the matched datasets varied and ranged from 4,880 (the first imputed dataset) to 4,910 (the fifth imputed dataset). This variation was due to differences in the common support areas (i.e., area of overlap in the distribution of propensity scores for control and treated participants). That is, some control and treated participants were outside of the common support areas indicating that they did not match a counterpart participant and, therefore, they were excluded. There was no variation in sample size across the imputed datasets for the unmatched sample. This is because the entire analytic sample was used when imputing and analyzing the unmatched data rather than participants being matched and excluded if they were not matched. Figure 1 depicts the distributions of the estimated propensity scores in the treatment and control groups before and after matching for the first imputed dataset. The distributions of the estimated propensity scores in the treatment and control

³There was no missing data for the advanced math course taking variable because we restricted the analytic sample to students with valid high school transcript information.

groups after matching were much similar than those before matching. This indicated that there was little difference in the preexisting observed covariates after matching.⁴

As mentioned, we next completed the three models in the OLS, logistic, and multinomial regression analyses and then replicated those models and analyses with the matched sample. Though the interaction terms in the third model examined variation in effects for the unmatched and matched samples, we also conducted propensity score analyses with one demographic group at a time to investigate the differing effects of advanced math course taking by SES and race/ethnicity. The findings are not reported here but they were similar to those discussed in the results sections that follow. Because we were interested in the effect of advanced math course taking before and after controlling for the covariates and variation in effects by SES and race/ethnicity, the coefficients for all other covariates are omitted from the next sections and corresponding tables for brevity.

Effect on Math Achievement

For the unmatched sample, Model 1 showed a significant positive effect of advanced math course taking on math achievement ($b = 39.78$, $R^2 = .34$; Table 3). Specifically, taking advanced math courses increased math achievement by approximately 40 points. When the other covariates were entered in Model 2, the effect size of advanced math course taking was reduced to 7.79 (approximately 80% reduction). This result suggested that much of the observed effect of advanced math course taking was due to preexisting differences between students who did take advanced math courses and students who did not. Adding the interaction terms in Model 3 showed some socioeconomic and racial/ethnic variation in the effect of advanced math course taking. Specifically, advanced math course taking had a greater impact for low SES students than high SES students, but a smaller impact for Black students than for White students.

For the matched sample, Model 1 showed a significant but much smaller effect on and amount of variance explained in ($b = 6.29$, $R^2 = .01$) math achievement compared to Model 1 for the unmatched sample ($b = 39.78$, $R^2 = .34$). Specifically, taking advanced math courses increased math achievement by approximately 6 points. This difference in the magnitude of the effects of advanced math course taking in Model 1 between the matched and unmatched samples was due to the fact that we used the covariates in the matching process to address selection effects. In Model 2, we additionally controlled for these covariates for the matched sample and found showed a significant effect ($b = 7.37$, $R^2 = .69$). In Model 3, we additionally introduced the interaction terms and found that there were differing effects of advanced math course taking by SES and race/ethnicity. Specifically, as Model 3 for the unmatched sample showed, results indicated that low SES and White students benefited more from advanced math course taking than high SES and Black students. Figure 2 and 3 depict these differential effects of advanced math course taking on math achievement among students of diverse socioeconomic and racial/ethnic backgrounds, respectively.

⁴We also conducted a t-test or chi-square test for the covariates (not shown) to check the balance of the propensity scores with each of the five matched datasets, and found no systematic difference in the covariates between the treated and control participants.

Effect on College Enrollment

College enrollment—For the unmatched sample, Model 1 (included advanced math course taking only) showed a significant effect of advanced math course taking on college enrollment ($b = 2.11$, $OR = 8.25$, $\text{pseudo } R^2 = .14$). Specifically, the odds of being enrolled in college were approximately eight times higher for students who took advanced math courses than for students who did not. When the other covariates were controlled in Model 2, the effect size of advanced math course taking was reduced to $b = 0.70$ ($OR = 2.01$). Model 3 showed no significant SES and racial/ethnic differences in the effects of advanced math course taking.

With the matched sample, Model 1 also showed that advanced math course taking had a significant effect on college enrollment ($b = 0.54$, $OR = 1.72$). The odds of being enrolled in college were approximately two times higher for students who took advanced math courses than for students who did not. Model 2 that additionally included the covariates with the matched sample showed similar effects of advanced math course taking ($b = 0.69$, $OR = 1.99$). Like Model 3 for the unmatched sample, there was no significant interaction with SES and race/ethnicity in Model 3 for the matched sample.

Type of college enrollment—For the unmatched sample, Model 1 showed a significant effect of advanced math course taking on enrollment in a 2- and 4-year college, respectively. For the 4-year college enrollment, for example, the odds of being enrolled in 4-year college, rather than no college enrollment, were almost 17 times higher for students who took advanced math courses than for students who did not ($b = 2.83$, $OR = 16.95$). When the covariates were added (Model 2), these gaps were substantially reduced (e.g., from 2.83 to 0.76 for 4-year college). Model 3 showed some socioeconomic differences in the effect of advanced math course taking with a greater impact for low SES students than high SES students.

For the matched sample, Model 1 showed a significant effect of advanced math course taking only on the 4-year college enrollment, but not on the 2-year college enrollment. Specifically, the odds of being enrolled in 4-year college, rather than no college enrollment, were proximately two times higher for students who take advanced math courses than for students who did not ($b = .76$, $OR = 2.14$). However, when the covariates were added in Model 2, there was a significant effect of advanced math course taking on both 2- and 4-year college enrollments. In Model 3, there were no significant socioeconomic differences in the effects of advanced math course taking.

Sensitivity Analyses

Table 6 presents the results from our Rosenbaum bounds sensitivity analyses across the five imputed datasets. Γ is the Rosenbaum bounds estimate of the magnitude of selection bias on an unobserved covariate that would predict advanced math course taking, expressed as an odds ratio. An odds ratio of 1 implies that an unobserved confounding variable does not affect treatment assignment. The p -critical presents the upper bound of the p value from Wilcoxon signed rank tests for the averaged treatment effect on the treated for each level of bias.

As for math achievement, the critical level of Γ that would call into question our finding of a positive treatment effect was between 1.4 and 1.5 for all imputed datasets. This suggested that an unobserved variable would have to increase a student's odds of treatment by 40% to 50% to eliminate the positive effect of advanced math course taking on math achievement. A selection bias with such magnitude was larger than the estimated net effect of being in the college prep track (OR = 1.30) instead of being in the vocational track (see Table 2). Therefore, the effect of an unobserved variable should be larger than the effects of being in the college prep track after controlling for all other covariates included in Table 2.

The Rosenbaum bounds for college enrollment suggested that Γ should be at least between 1.3 and 1.6 to nullify the positive effect of advanced math course taking. Again, these magnitudes were larger than or comparable to the effect of being in the college prep track instead of being in the vocational track. In sum, sensitivity analyses suggested that selection bias due to unobserved covariates would have to be quite substantial to completely eliminate the matched sample estimates of the positive effect of advanced math course taking.

Discussion

The current study contributes to previous research on the effects of advanced math course taking in several respects. First, although selection bias is a major concern when examining the effect of advanced course taking, most research has also only accounted for a small number of student-level covariates and only a few studies have used more robust methods such as PSM to estimate the effect of advanced math course taking. Furthermore, the current study extends previous PSM studies by using more recent, longitudinal, and nationally representative data from the ELS:02/06. Second, previous research has largely focused on the average effect of advanced math course taking. The current study adds to the literature base by examining differential effects for students of diverse SES and racial/ethnic backgrounds.

One of the key findings was that regardless of the methods used, advanced math course taking had a significant, positive effect on math achievement and college enrollment. Sensitivity analyses confirmed that the positive effect of advanced math course taking on math achievement and college enrollment was relatively free of hidden bias. Findings of a positive effect of advanced math course taking were consistent with previous PSM research (Leow et al., 2004; Long et al. 2012). Yet, our results indicated that the strong relationship between advanced math course taking and student outcomes were largely due to other student, family, and school factors rather than advanced math course taking itself. This is because the effect of advanced math course taking was substantially reduced when covariates were added in regression analyses and PSM was used. This finding highlights the importance of taking into account a comprehensive set of student- and school-level characteristics when studying the effect of advanced math course taking.

Another important finding was that there were some racial/ethnic and SES differentials in the effect of advanced math course taking on math achievement. Specifically, advanced math course taking had a smaller effect on math achievement for Black students than White students. Similarly, Long et al. (2009) found a smaller effect of advanced math course taking

on college math readiness for Black students among public university students in Florida. When it came to SES differentials, however, we found that advanced math course taking had a greater effect on math achievement for low SES than high SES students. This finding is inconsistent with that of Long et al. (2009)'s study, which reported a smaller effect of advanced math course taking on college math readiness for low SES students.

Finally, while showing the significant effect on college enrollment especially for 4-year college, our findings demonstrated that the effect of advanced math course taking on college enrollment did not vary across SES and racial/ethnic backgrounds. Our results were different from those of Long et al. (2012) which indicated that there was a stronger effect of advanced math course taking on 2-year college enrollment for youth from low SES, African American, and Hispanic backgrounds but a weaker effect on 4-year college enrollment for youth from low SES backgrounds. However, the insignificant interactions in our results suggest that advanced math course taking has a comparable effect on college enrollment for youth from low SES and racial/ethnic minority backgrounds.

Limitations of the Study and Directions for Future Research

The current study has some limitations which should be considered. First, we focused on math only and used a dichotomous measure of advanced math course taking. Previous research has found a positive effect of taking a higher level course in and curricular intensity of other subjects such as science and English (Attewell & Domina, 2008; Schneider et al., 1998). In addition, results from Long et al. (2012) suggest that taking advanced courses in other subjects may interact with and provide additional benefits to taking advanced math courses. Consequently, research on advanced math course taking may provide additional insights by considering course taking in other subjects and examining interactive or additive effects.

Second, although we found some differential effects of advanced math course taking by SES and race/ethnicity, it is still unclear why the effects of advanced math course taking differ depending on SES and race/ethnicity. Some scholars have suggested that the quality of advanced courses available to students may vary and be a factor in the differential effects for students from different socioeconomic and racial/ethnic backgrounds (Adelman, 2006; Riegle-Crumb & Grodsky, 2010; Schneider et al., 1998). Indeed, it is well known that low-income and ethnic minority students are more likely than high-income and majority students to be taught by uncertified teachers (Ascher & Fruchter, 2001; Darling-Hammond, 2004), out-of-field teachers (i.e., those without a major in the subject they teach; Ingersoll, 2002; Jerald & Ingersoll, 2002), or teachers with low ACT or SAT scores (Shen, Mansberger, & Yang, 2004). These socioeconomic and racial/ethnic inequalities in access to qualified teachers may be responsible for the differing effect of advanced math course taking by SES and race/ethnicity. However, the current study did not have data on and was not able to test how the quality of teachers who teach the advanced math courses and the quality of the advanced math courses offered differ by students of diverse backgrounds. Therefore, future studies should integrate both the intensity and quality of advanced courses as well as consider other subjects to offer more nuanced evidence on the effect of advanced course taking.

Third, we used only one approach for estimating causal effects from correlational data (i.e., PSM). There are other methods that can be used to estimate the causal effect of advanced math course taking. Though often considered difficult to implement, instrumental variable estimation is one other method that could be used to address selection bias. Employing additional methods that are more robust to selection effects would further support the soundness of our results.

Finally, we used data from the ELS:02/06. Thus, our results may not reflect recent course taking patterns among American high school students and results should be carefully interpreted when generalizing to a more recent cohort of high school students. However, data from the ELS:02/06 is the most recent, longitudinal, and nationally representative data available for research across high school and into the postsecondary years. Nonetheless, future research should use more recent data (e.g., High School Longitudinal Study of 2009) to document contemporary course taking patterns.⁵

Policy Implications and Additional Directions for Future Research

Results from the use of PSM and sensitivity analyses indicate that there is a causal effect of advanced math course taking. The more modest effect of advanced math course taking that was evident in our PSM results as compared to our regression analyses with the unmatched sample suggests that the taking of advanced courses may provide smaller benefits than results from regression analyses indicate. Therefore, efforts to promote and research on educational attainment may need to attend to and identify additional contributory factors. Our findings regarding the variation in the more beneficial effect of advanced math course taking for students from low SES backgrounds and the lack of differential effects on college enrollment support policies and efforts to increase access. Yet, one interactive effect is concerning and that is the smaller effect of advanced math course taking on the math achievement of Black students. This finding support the notion that “the advanced courses available to underrepresented youth are advanced in name but not in substance” (Riegle-Crumb & Grodsky, 2010, p.249).

Yet, in our view, several issues indicate that at this point it would be too early to draw definitive conclusions and implications from these findings. For one, only limited research has thus far examined differences in the effects of advanced course taking by SES and race/ethnicity. Furthermore, the findings across these few studies have varied and this could be due to one or a combination of several factors. These include differences in outcome variables (e.g., 12th grade math achievement, college math readiness), samples (e.g., college students in Florida, nationally representative samples from the 1990s and 2000s), and advanced course taking measures (e.g., math course taking, more general curricular intensity).

Clearly, more research is needed before such findings should inform policy. Specifically, we need to replicate and better understand the underlying reasons for similar and contradictory

⁵The High School Longitudinal Study of 2009 (HSL:09) followed a nationally representative sample of 9th graders in 2009 but we did not use it because only its first follow-up data (11th grade) were available when we conducted the current study. Therefore, with the HSL:09 data, we were unable to examine the college enrollment outcomes.

results. Furthermore, the research by Riegle-Crumb and Grodsky (2010) suggests that the underlying factors and processes may be quite complex, especially for those taking advanced courses. For example, Riegle-Crumb and Grodsky (2010) found more variation in the role of SES and race/ethnicity for math achievement among students taking advanced math courses versus those that do not take advanced math courses. Moreover, within students taking advanced courses the background and other factors that may contribute to their achievement was different between African American and Hispanic youth. In sum, future research and policy may need to acknowledge that the effects of advanced math course taking could be more complex than most have assumed thus far. However, more research is needed before these conclusions can be more definitive.

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Appendix A

Description of Variables

Variable	Description	% imputed
Outcome variables		
Math achievement ^a	Continuous measure of the number of items the student would have answered correctly had he/she taken the entire mathematics test (based on students' IRT scale score) administered to all survey participants in the 12th grade	12.0
College enrollment ^b	Dichotomous indicator of whether the student was ever enrolled in a degree-granting postsecondary education institution; reference: no enrollment	0.2
Type of college enrollment ^b	Trichotomous indicator of which type of degree-granting postsecondary education institution the student was enrolled in; no enrollment (reference), 2-year college enrollment, and 4-year college enrollment	0.2
Treatment variable		
Advanced math course taking ^a	Dichotomous indicator of whether the student ever took an advanced math course, as evidenced by transcript information; reference: did not take advanced math courses	—
Covariates		
SES ^a	Composite measure of socioeconomic status, derived from parental education, income, and occupation when in the 10th grade, and provided by the ELS.	0.0
Two-parent family ^c	Dichotomous measure of whether the student lived with biological mother and father when in the 10th grade; other (reference)	0.0
Number of siblings ^c	Continuous measure of the number of siblings when in the 10th grade	16.4
Parental educational expectation ^c	Continuous measure of parents' expectation of the surveyed child's education when in the 10th grade; range from 1 = less than high school graduation to 7 = obtain PhD, MD, or other advanced degree	0.0
Parent-child discussion ^b	Factor composite (average) of eight student responses about discussion on academic work with their parents when in the 10th grade	19.6
Parent contact school ^c	Factor composite (average) of three parent responses about their contact with school when in the 10 th grade	20.3
Parent-parent interaction ^c	Factor composite (average) of four parent responses about their interaction with parents of friends of their child when in the 10th grade	19.8
Race/ethnicity ^b	Categorical measure of the student's race; Asian, black, Hispanic, white (reference), and more than one race	0.0
Female ^b	Dichotomous indicator the student's gender; reference: male	0.0
Student educational expectations ^b	Continuous measure of the student's expectation of education when in the tenth grade; Range from 1 = less than high school graduation to 7 = obtain PhD, MD, or other advanced degree	9.1

Variable	Description	% imputed
ESL ^b	Dichotomous indicator of whether the student was ever in an English as Second Language (ESL) program; reference: no ESL program	5.9
Previous math achievement ^a	Continuous measure of the number of items the student would have answered correctly had he/she taken the entire mathematics test (based on students' IRT scale score) administered to all survey participants in the 10th grade	0.0
Previous reading achievement ^a	Continuous measure of the number of items the student would have answered correctly had he/she taken the entire reading test (based on students' IRT scale score) administered to all survey participants in the 10th grade	0.0
Previous GPA ^a	Continuous measure of grade point average (GPA) for all 10th grade courses based on a four-point scale (A = 4.0; F = 0.0)	0.8
Student employment ^b	Dichotomous indicator of whether the student ever worked for pay when in the 10th grade; reference: no paid work	14.5
Time spent on homework ^b	Continuous measure of the student's hours (per week) spent on homework out of school when in the 10th grade; Range from 0 to 26	2.3
Track ^b	Categorical measure of the student's high school track; general, college prep, and vocational (reference)	0.0
Teacher expectations ^d	Continuous measure of the teacher's expectation of education of the student when in the 10th grade; Range from 1 = less than high school graduation to 7 = obtain PhD, MD, or other advanced degree	24.1
Motivation/engagement ^d	Factor composite (average) of five teacher responses about their perception of school behavior of the student when in the 10th grade	23.8
% of free lunch ^a	Continuous measure of the percent of free lunch students based on the 2001–2002 Common Code of Data and Private School Survey and provided by the National Center for Education Statistics	30.0
% of minority ^a	Continuous measure of the percent of minority students based on the 2001–2002 Common Code of Data and Private School Survey and provided by National Center for Education Statistics	1.8
School sector ^e	Categorical measure of the school sector; public (reference), catholic, and other private	0.0
Urbanicity ^e	Categorical measure of urbanicity; urban, suburban, and rural (reference)	0.0

^aTranscript data or other sources provided by the National Center for Educational Science.

^bStudent questionnaire.

^cParent questionnaire.

^dTeacher questionnaire.

^eSchool administrator questionnaire, SES = socioeconomic status. ESL = English as a second language.

Appendix B

Description of Original Items and Scales for Composite Variables

Short description of variable	Full description (original scale)	α	% variance explained by items	Factor loadings
Parent-child discussion ^a	In the first semester or term of this school year, how often have you discussed the following with either or both of your parents or guardians? (1 = never, 2 = sometimes, 3 = often)	0.85	0.5	
	(1) Selecting courses or programs at school			0.75

Short description of variable	Full description (original scale)	α	% variance explained by items	Factor loadings
Parent contact school ^b	(2) School activities or events of particular interest to you	0.71	0.65	0.75
	(3) Things you've studied in class			0.78
	(4) Your grades			0.7
	(5) Plans and preparation for ACT or SAT tests			0.66
	(6) Going to college			0.73
	(7) Community, national and world events			0.66
	(8) Things that are troubling you			0.62
	Since your tenth grader's school opened last fall, how many times have you or your spouse/partner contacted the school about the following? (1 = none, 2 = once or twice, 3 = three or four times, 4 = more than four times)			
Parent-parent interaction ^b	(1) Your tenth grader's school program for this year	0.75	0.57	0.73
	(2) Your tenth grader's plans after leaving high school			0.84
	(3) Your tenth grader's course selection for entry into college, vocational, or technical school after completing high school			0.84
	Looking back over the past year, how many times did the following occur? The parent(s) of one of my tenth grader's friends ... (1 = none, 2 = once or twice, 3 = three or four times, 4 = more than four times)			
	(1) gave me advice about teachers and/or courses at my tenth grader's school			0.63
	(2) did me a favor			0.89
	(3) received a favor from me			0.87
	(4) supervised my tenth grader on an educational outing or field trip			0.58
Motivation/engagement ^c		0.78	0.54	
	(1) How often does this student complete homework assignments for your class?			0.81
	(2) How often is this student absent from your class? (1 = never, 2 = rarely, 3 = some of the time, 4 = most of the time, 5 = all of the time) ; codes reversed			0.64
	(3) How often is this student tardy to your class? (1 = never, 2 = rarely, 3 = some of the time, 4 = most of the time, 5 = all of the time) ; codes reversed			0.71
	(4) How often is this student attentive in your class? (1 = never, 2 = rarely, 3 = some of the time, 4 = most of the time, 5 = all of the time)			0.82
	(5) How often is this student disruptive in your class? (1 = never, 2 = rarely, 3 = some of the time, 4 = most of the time, 5 = all of the time) ; codes reversed			0.67

Note: Factor analysis results are based on one complete and unweighted dataset.

^a Student questionnaire.

^b Parent questionnaire.

^c Teacher questionnaire.

^d School administrator questionnaire.

Figure 1.
The Distributions of the Estimated Propensity Scores in the Treatment and Control Groups
Before and After Matching
Note: Boxplots based on the first imputed dataset. 0 = control group, 1 = treatment group

Figure 2.

The Differential Effects of Advanced Math Course Taking on Math Achievement for Students of Diverse Socioeconomic Background

Note: Figure based on Model 3 in Table 3 for the matched sample.

Figure 3.

The Differential Effects of Advanced Math Course Taking on Math Achievement for White and Black Students

Note: Figure based on Model 3 in Table 3 for the matched sample.

Table 1
Weighted Descriptive Statistics of Variables by Advanced Math Course Taking: Full Sample

Variable	Total		Advanced math course taking		Non-advanced math course taking		Sig. test
	Mean or proportion	(SE)	Mean or proportion	(SE)	Mean or proportion	(SE)	
Outcome variables							
Math achievement	148.83	(0.38)	171.05	(0.45)	131.28	(0.42)	***
Enrolled in any college	0.72	0.00	0.91	0.00	0.56	0.01	***
Enrolled in any 2-year college	0.27	0.00	0.18	0.01	0.34	0.01	***
Enrolled in any 4-year college	0.45	0.01	0.73	0.01	0.22	0.01	***
Covariates							
SES	0.01	(0.01)	0.28	(0.01)	-0.21	(0.01)	***
Two-parent family	0.58	(0.01)	0.68	(0.01)	0.51	(0.01)	***
Number of siblings	2.34	(0.02)	2.07	(0.02)	2.56	(0.02)	***
Parental educational expectation	5.33	(0.01)	5.70	(0.02)	5.04	(0.02)	***
Parent-child discussion	2.09	(0.01)	2.22	(0.01)	1.99	(0.01)	***
Parent contact school	1.34	(0.01)	1.35	(0.01)	1.33	(0.01)	
Parent-parent interaction	1.85	(0.01)	1.95	(0.01)	1.76	(0.01)	***
Race/ethnicity							
Asian	0.04	(0.00)	0.06	(0.00)	0.03	(0.00)	***
Black	0.14	(0.00)	0.10	(0.00)	0.16	(0.01)	***
Hispanic	0.15	(0.00)	0.09	(0.00)	0.20	(0.01)	***
White	0.63	(0.01)	0.71	(0.01)	0.56	(0.01)	***
Multiracial	0.05	(0.00)	0.04	(0.00)	0.05	(0.00)	*
Female	0.51	(0.01)	0.53	(0.01)	0.49	(0.01)	***
Student educational expectations	5.10	(0.02)	5.68	(0.02)	4.64	(0.02)	***
ESL	0.08	(0.00)	0.05	(0.00)	0.10	(0.00)	***
Previous math achievement	50.57	(0.11)	56.35	(0.14)	46.00	(0.13)	***
Previous reading achievement	50.54	(0.11)	55.59	(0.14)	46.56	(0.14)	***
Previous GPA	2.64	(0.01)	3.16	(0.01)	2.23	(0.01)	***
Student employment	0.39	(0.01)	0.37	(0.01)	0.40	(0.01)	**

Variable	Total		Advanced math course taking		Non-advanced math course taking		Sig. test
	Mean or proportion	(SE)	Mean or proportion	(SE)	Mean or proportion	(SE)	
Time spent on homework	5.73	(0.06)	7.22	(0.10)	4.56	(0.08)	***
Track							
General	0.38	(0.01)	0.27	(0.01)	0.47	(0.01)	***
College prep	0.52	(0.01)	0.67	(0.01)	0.40	(0.01)	***
Vocational	0.10	(0.00)	0.06	(0.00)	0.13	(0.01)	***
Teacher expectations	4.07	(0.02)	4.93	(0.02)	3.39	(0.02)	***
Motivation/engagement	4.09	(0.01)	4.35	(0.01)	3.89	(0.01)	***
% of free lunch	21.66	(0.20)	17.82	(0.28)	24.69	(0.28)	***
% of minority	33.40	(0.32)	29.84	(0.45)	36.21	(0.45)	***
School sector							
Public	0.92	(0.00)	0.87	(0.00)	0.96	(0.00)	***
Catholic	0.05	(0.00)	0.07	(0.00)	0.02	(0.00)	***
Other private	0.03	(0.00)	0.05	(0.00)	0.02	(0.00)	***
Urbanicity							
Urban	0.29	(0.00)	0.30	(0.01)	0.28	(0.01)	*
Suburban	0.52	(0.01)	0.52	(0.01)	0.51	(0.01)	
Rural	0.20	(0.00)	0.18	(0.01)	0.21	(0.01)	***
Unweighted N	12,250		6,020		6,240		

SES = socioeconomic status. ESL = English as a second language.

*** p<.001,

** p<.01,

* p<.05 (two-tailed tests)

Table 2

Results from Logistic Regression Model Predicting Advanced Math Course Taking (N = 12,250)

Covariate	Coef.		(SE)	OR
SES	0.14	*	(0.05)	1.15
Two-parent family	0.13		(0.06)	1.13
Number of siblings	−0.08	***	(0.02)	0.92
Parental educational expectation	0.06		(0.03)	1.06
Parent-child discussion	0.08		(0.07)	1.08
Parent contact school	0.03		(0.07)	1.03
Parent-parent interaction	0.04		(0.05)	1.04
Race/ethnicity (white omitted)				
Asian	0.18		(0.13)	1.20
Black	0.58	***	(0.14)	1.78
Hispanic	−0.23		(0.12)	0.80
Multiracial	−0.04		(0.14)	0.96
Female	−0.09		(0.06)	0.91
Student educational expectations	0.14	***	(0.03)	1.15
ESL	0.02		(0.12)	1.02
Previous math achievement	0.08	***	(0.01)	1.08
Previous reading achievement	0.00		(0.01)	1.00
Previous GPA	0.91	***	(0.08)	2.50
Student employment	−0.06		(0.07)	0.94
Time spent on homework	0.02	***	(0.01)	1.02
Track (vocational omitted)				
General	−0.10		(0.13)	0.90
College prep	0.26	*	(0.12)	1.30
Teacher expectations	0.24	***	(0.04)	1.27
Motivation/engagement	0.05		(0.08)	1.05
% of free lunch	−0.01	*	(0.00)	0.99
% of minority	0.01	*	(0.00)	1.01
School sector (public omitted)				
Catholic	0.51	**	(0.16)	1.67
Other private	0.00		(0.19)	1.00
Urbanicity (rural omitted)				
Urban	0.47	**	(0.16)	1.60
Suburban	0.17		(0.13)	1.18
Constant	−9.70		(0.51)	
Log likelihood	−5369.73			
Pseudo (McFadden's) R^2	0.36			

Note: The estimates are an average of the results across the five complete, weighted datasets by using Rubin's (1987) rule. Standard errors are corrected for clustering within schools.

SES = socioeconomic status. ESL = English as a second language.

p<.001,
**
p<.01,
*
p<.05 (two-tailed tests)

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Table 3

Results from OLS Regression Models Predicting Math Achievement

Variable	Unmatched Data				Matched Data			
	Model 1 (+ advanced course taking only)	Model 2 (Model 1+ SES, race/ethnicity, and other covariates ^a)	Model 3 (Model 2+ interaction terms for SES and race/ethnicity)	Model 1 (+ advanced course taking only)	Model 2 (Model 1+ SES, race/ethnicity, and other covariates ^a)	Model 3 (Model 2+ interaction terms for SES and race/ethnicity)	Coef.	(SE)
Advanced math course taking	39.78 *** (0.83)	7.79 *** (0.51)	8.90 *** (0.57)	6.29 *** (1.23)	7.37 *** (0.59)	8.67 *** (0.78)		
SES		1.28 *** (0.27)	1.75 *** (0.37)		1.25 * (0.55)	2.32 *** (0.63)		
Race/ethnicity (white omitted)								
Asian		2.07 ** (0.72)	0.96 (1.23)		1.37 (1.27)	1.60 (1.83)		
Black		-1.47 * (0.60)	0.37 (0.70)		-2.06 (1.12)	0.31 (1.36)		
Hispanic		0.41 (0.57)	1.08 (0.73)		-0.35 (0.94)	0.52 (1.34)		
Multiracial		0.05 (0.87)	0.82 (1.06)		0.58 (1.38)	2.32 (2.24)		
Advanced math course taking × SES			-1.06 * (0.51)			-2.15 * (0.92)		
Advanced math course taking × Asian			1.51 (1.36)			-0.85 (2.86)		
Advanced math course taking × Black			-5.29 *** (0.99)			-5.26 *** (1.48)		
Advanced math course taking × Hispanic			-1.79 (1.15)			-2.01 (2.02)		
Advanced math course taking × Multiracial			-1.81 (1.70)			-3.30 (3.33)		
Constant	131.28 *** (0.61)	8.84 *** (2.21)	8.92 *** (2.23)	147.24 *** (0.81)	5.65 (4.39)	5.68 (4.49)		
R^2 ^b	0.34	0.83	0.83	0.01	0.69	0.69		

Note: The estimates for the unmatched and matched results are an average of the results across the five complete, weighted datasets by using Rubin's (1987) rule. Standard errors are corrected for clustering within schools. The sample size for unmatched data was 12,250 across the five imputed datasets. The sample sizes for matching estimates ranged from 4,880 (the first imputed dataset) to 4,910 (the fifth imputed dataset) due to differences in the common support areas.

^a . Other covariates include family structure, number of siblings, parental educational expectation, parent-child discussion, parent contact school, parent-parent interaction, gender, student educational expectations, English as a second language, previous math achievement, previous reading achievement, previous GPA, student employment, time spent on homework, track, teacher expectations, teacher motivation/engagement, % of free lunch, % of minority, school sector, and urbanicity. For the sake of brevity results for these covariates are not included.

^b . R^2 based on one complete and weighted dataset.

p<.001,

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Table 4

Results from Logistic Regression Models Predicting College Enrollment

Variable	Unmatched Data					Matched Data									
	Model 1 (+ advanced course taking only)		Model 2 (Model 1 + SES, race/ethnicity, and other covariates ^d)			Model 3 (Model 2+ interaction terms for SES and race/ethnicity)		Model 1 (+ advanced course taking only)		Model 2 (Model 1 + SES, race/ethnicity, and other covariates ^d)		Model 3 (Model 2+ interaction terms for SES and race/ethnicity)			
	Coef.	(SE)	Coef.	(SE)	OR	Coef.	(SE)	OR	Coef.	(SE)	Coef.	(SE)	OR		
Advanced math course taking	2.11	*** (0.08)	0.70	*** (0.09)	0.74	*** (0.11)	2.10		0.54	*** (0.11)	0.69	*** (0.13)	0.69	*** (0.14)	1.99
SES			0.54	*** (0.06)	0.52	*** (0.07)	1.68				0.54	*** (0.10)	0.50	*** (0.14)	1.65
Race/ethnicity (white omitted)															
Asian			0.52	** (0.16)	0.48	** (0.20)	1.61				0.32	(0.26)	0.14	(0.34)	1.15
Black			0.42	*** (0.11)	0.46	*** (0.12)	1.58				0.44	*	0.55	*	1.73
Hispanic			0.27	*	0.28	*	1.32				0.20	(0.22)	0.11	(0.28)	1.12
Multiracial			-0.29	(0.15)	-0.28	(0.17)	0.75				-0.24	(0.31)	-0.28	(0.48)	0.76
Advanced math course taking × SES					0.08	(0.12)	1.08						0.10	(0.18)	1.10
Advanced math course taking × Asian					0.13	(0.28)	1.14						0.49	(0.45)	1.63
Advanced math course taking × Black					-0.14	(0.21)	0.87						-0.23	(0.29)	0.80
Advanced math course taking × Hispanic					-0.06	(0.24)	0.94						0.22	(0.38)	1.24
Advanced math course taking × Multiracial					-0.01	(0.37)	0.99						0.08	(0.61)	1.09
Constant	0.26	*** (0.04)	-5.25	*** (0.41)	-5.24	*** (0.41)	-		1.17	*** (0.07)	-5.10	*** (1.02)	-5.04	*** (1.01)	-
Log likelihood ^b	-6267.03		-4969.12		-4968.12		-2399.56		-1989.15		-1984.89				
Pseudo (McFadden's) <i>R</i> ^{2b}	0.14		0.32		0.32		0.01		0.18		0.18				

Note: The estimates for the unmatched and matched results are an average of the results across the five complete, weighted datasets by using Rubin's (1987) rule. Standard errors are corrected for clustering within schools. The sample size for unmatched data was 12,250 across the five imputed datasets. The sample sizes for matching estimates ranged from 4,880 (the first imputed dataset) to 4,910 (the fifth imputed dataset) due to differences in the common support areas.

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^d Other covariates include family structure, number of siblings, parental educational expectation, parent-child discussion, parent contact school, parent-parent interaction, gender, student educational expectations, English as a second language, previous math achievement, previous reading achievement, previous GPA, student employment, time spent on homework, track, teacher expectations, teacher motivation/engagement, % of free lunch, % of minority, school sector, and urbanicity. For the sake of brevity results for these covariates are not included.

^q Loglikelihood and Pseudo R^2 based on one complete and weighted dataset.

p<.001,
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p<.01,
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p<.05 (two-tailed tests)

Table 5
Results from Multinomial Logistic Regression Models Predicting the Type of College Enrollment

Unmatched Data												
Variable	Model 1 (+ advanced course taking only)			Model 2 (Model 1 + SES, race/ethnicity, and other covariates ^d)			Model 3 (Model 2 + interaction terms for SES and race/ethnicity)					
	2-year	4-year		2-year	4-year		2-year	4-year		2-year	4-year	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)	OR	(SE)	OR	(SE)
Advanced math course taking	0.99 ***	(0.09)	2.83 ***	(0.09)	0.26 *	(0.10)	1.05 ***	(0.10)	0.23 *	(0.12)	1.12	(0.12)
SES					0.36 ***	(0.06)	0.83 ***	(0.07)	0.42 ***	(0.07)	1.07	(0.08)
Race/ethnicity (white omitted)												
Asian					0.50 **	(0.17)	0.53 **	(0.17)	0.52 **	(0.19)	1.21	(0.25)
Black					0.17	(0.12)	1.00 ***	(0.14)	0.18	(0.12)	1.13	(0.16)
Hispanic					0.26 *	(0.11)	0.16	(0.14)	0.24 *	(0.12)	1.13	(0.17)
Multiracial					-0.46 **	(0.16)	0.02	(0.19)	-0.39 *	(0.17)	1.19	(0.26)
Advanced math course taking × SES							-0.27 *	(0.13)	-0.06	(0.14)	0.94	(0.14)
Advanced math course taking × Asian							-0.05	(0.29)	0.38	(0.34)	1.46	(0.34)
Advanced math course taking × Black							-0.10	(0.25)	-0.24	(0.25)	0.79	(0.25)
Advanced math course taking × Hispanic							0.12	(0.25)	-0.10	(0.29)	0.90	(0.29)
Advanced math course taking × Multiracial							-0.38	(0.43)	-0.02	(0.46)	0.98	(0.46)
Constant	-0.23 ***	(0.04)	-0.68 ***	(0.05)	-3.75 ***	(0.42)	-10.48 ***	(0.60)	-3.72 ***	(0.42)	-	(0.60)
Log likelihood ^b	-11326.09			-9227.29			-9216.32					
Pseudo (McFadden's) R^2 ^b	0.14			0.30			0.30					
Advanced math course taking	0.22	(0.13)	0.76 **	(0.12)	0.36 *	(0.15)	1.09 ***	(0.13)	0.34 *	(0.16)	1.41	(0.15)
SES					0.31 **	(0.11)	0.81 ***	(0.11)	0.29 ***	(0.14)	1.33	(0.15)
Race/ethnicity (white omitted)												

Note: The estimates for the unmatched and matched results are an average of the results across the five complete, weighted datasets by using Rubin's (1987) rule. Standard errors are corrected for clustering within schools. The sample size for unmatched data was 12,250 across the five imputed datasets. The sample sizes for matching estimates ranged from 4,880 (the first imputed dataset) to 4,910 (the fifth imputed dataset) due to differences in the common support areas. The base category is no college enrollment.

²: Loglikelihood and Pseudo R^2 based on one complete and weighted dataset.

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Sensitivity Analyses Using Rosenbaum bounds of the Causal Effects of Advanced Math Course Taking across Imputed Datasets

Table 6

Imputed dataset											
		1		2		3		4		5	
Outcome variable	Γ	p -critical	Γ	p -critical	Γ	p -critical	Γ	p -critical	Γ	p -critical	
Math achievement	1.3	0.000	1.3	0.000	1.3	0.000	1.3	0.000	1.3	0.000	
	1.4	0.027	1.4	0.038	1.4	0.003	1.4	0.016	1.4	0.040	
	1.5	0.315	1.5	0.371	1.5	0.103	1.5	0.245	1.5	0.382	
College enrollment	1.0	0.000	1.0	0.000	1.0	0.000	1.0	0.000	1.0	0.000	
	1.3	0.001	1.3	0.001	1.3	0.000	1.3	0.003	1.3	0.001	
	1.6	0.361	1.6	0.379	1.6	0.251	1.6	0.472	1.6	0.316	

Note: Γ is the odds ratio of differential treatment assignment due to an unobserved covariate. p -critical from the Wilcoxon signed rank tests.