Estimating the Impact of Growth Mindset on High School Mathematics Performance and Course-Taking¹

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Abstract

Using a randomized controlled trial in a nationally representative sample of 65 public high schools ($N = 13,660$), we tested the effects of a growth mindset intervention on math course-taking patterns and student achievement and explored whether school context was related to the success of the intervention. Students were randomly assigned to complete either the growth mindset intervention or a control activity during two 25-minute sessions. After participating in the growth mindset program used in the National Study of Learning Mindsets, students' 9th-grade mathematics GPA increased by an average of 0.05 grade points on a 4.3-point scale. We found distinct patterns of treatment effects that depend on level of math preparation, course intensity, school context, and changes in students' mindset.

In high school, completion of advanced math courses improves students' likelihood of attending and completing postsecondary education—particularly at four-year institutions (Adelman, 1999; Kim, 2019; Kim et al., 2019; Riegle-Crumb, 2006; Schneider, Swanson, & Riegle-Crumb, 1998)—as well as their long-term labor market outcomes such as earnings, (Altonji, 1995; Goodman, 2019; Levine & Zimmerman, 1995; Rose & Betts, 2004) and risky health behaviors such as drinking, smoking, and marijuana use (Carroll et al., 2017; Hao & Cowan, 2019). Acknowledging the benefits of completing advanced math courses, many states and school districts have initiated interventions to improve math course-taking patterns and educational attainment. Yet, despite states' efforts to increase rigorous math course-taking, substantial racial and ethnic gaps in achievement and enrollment in advanced math courses have stubbornly persisted over the past two decades (Domina & Saldana, 2012; Kelly, 2009; Kim, 2018; Riegle-Crumb & Grodsky, 2010).

Growth mindset interventions have not yet been seriously investigated as an approach to increasing advanced math course-taking. These types of interventions deliver the message that students' intellectual abilities are not fixed and that their abilities can grow in response to

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increased efforts (Dweck, 2006; Yeager & Dweck, 2012); they are now capturing the attention of educational practitioners, as treatment conditions involve both relatively low respondent burden and cost to administer (Broda et al., 2018; Damgaard & Nielsen, 2018; Kim et al., 2020; Paunesku et al., 2015; Walton, 2014; Yeager & Dweck, 2012; Yeager & Walton, 2011; Yeager et al., 2016; Yun et al., 2018). Recently, the National Study of Learning Mindsets (NSLM) examined the effects of an online growth mindset intervention in a nationally representative sample of 9th-grade students in U.S. public schools and found that the intervention improved academic achievement among lower-achieving students (Yeager et al., 2019).

To estimate the causal effects of a growth mindset intervention on math course-taking, this study used NSLM data, which provide individual students' transcripts and thus more detailed information on course-taking, including enrollment history, credits, and grades. Using this detailed transcript data, we could identify every math course a student has taken and determine whether a mindset-treated student had a different course-taking outcome; this, in turn, provided more accurate information about an individual's educational trajectories.

This study estimated the impact of a growth mindset program on math course-taking outcomes in high school, such as grade point average (GPA) and course enrollment, and examined how effects differ based on students' incoming (8th-grade) math GPA, the intensity of the math course in which a student was enrolled, and school context related to growth mindset.

We report four sets of results. First, results indicate that after participating in the growth mindset program used in the NSLM, students' math GPA in 9th grade increased by an average of 0.05 points on a 4.3-point scale. The program effects were positive and significant for math, science, and STEM courses, whereas the effects were smaller and insignificant for English and social science courses. The effect size for math GPA was 0.05 points on a 4.3-point scale. Science and math were the subjects in which students improved the most after participating in the growth mindset program.

Second, effects of the program on math GPA were larger among two groups: a) students taking advanced courses in 9th grade (Geometry or Algebra II) and b) students taking Algebra I in 9th grade with a relatively high incoming math GPA. The program effects were positive and statistically significant for these two groups, whereas we found that there were no growth mindset program effects on math GPA for Algebra 1-takers—however, the benefit of the program appears to have varied as a function of students' math preparation, measured by 8th-grade math test scores. For example, program effects on math GPA were larger among more-prepared students, measured by 8th-grade standardized math test scores, and effects were minimal for less-prepared students taking Algebra I in 9th grade.

Third, the treatment effects on GPA were larger among treated students who attended schools where growth mindsets increased for control students. Results indicate that for schools where a larger fraction of control students showed increases in growth mindset *without* participating in the growth mindset program, students who *did* participate in the program showed above-average GPA improvement. In addition, the treatment was effective for students from schools in the middle of the self-reported mindset measure distribution (measured before the intervention), but not from schools at extreme points, such as those with a fixed mindset or already demonstrating a growth mindset.

Finally, we examined whether students who had the largest change in growth mindset showed different course-taking patterns and achievement compared to peers with smaller changes in growth mindset. This paper offers evidence that mindset intervention effects are linked to changes in individual mindset. In particular, the growth mindset program was effective for changing students' mindset, and students who changed more toward a growth mindset had higher treatment effects in terms of their GPA.

This study contributes to the literature by measuring the unbiased treatment effects across individuals and school context with a greater accuracy and generalizing the treatment effects to a population of 9th-grade students in 2015–16.² This study was the first to have used a nationally representative randomized sample of high schools to 1) show whether the effects of a growth mindset on math course-taking differed by school context or students' demographic and academic background; 2) demonstrate whether a growth mindset could predict subsequent course-taking and achievement; and 3) examine the extent to which changes in growth mindset could improve short-term course-taking outcomes.

Our study also contributes to the growing literature on evidence-based social and emotional learning (SEL) interventions. Although social and emotional skills are strong predictors of some long-term outcomes (e.g., Chetty et al., 2011; Deming, 2017; Jackson, 2018) and are malleable, this may not be true for everyone at all ages. In addition, growth mindset develops during early adolescence and tapers off in high school (West et al., 2018). Our findings show that the growth mindset treatment was effective for the high school students in our study, which can inform the decision-making of administrators and policymakers planning SEL interventions to support and improve students' outcomes.

Experimental Design

Intervention design

The NSLM was specifically designed to understand which kinds of 9th-grade students, in which kinds of classrooms and in which kinds of schools, are most likely to benefit from the growth mindset program. During the 2015–16 school year, the intervention was delivered at the beginning of high school through online sessions. At each school, 9th-graders were randomly assigned to complete either the growth mindset program or a control activity during two 25-minute sessions. In the growth mindset program, students read and listened to materials describing scientific evidence about how the brain works and why people are able to grow their intellectual abilities over time. The program encouraged students to think about why they might want to grow their brain in order to make a difference regarding something that matters to them, such as their family, community, or a social issue they care about. Control group students read a brief article about how the brain functions and completed writing exercises to summarize the article. Approximately 20 days later, both groups participated in a post-treatment online survey, with a median response rate of 98%.³

² Researchers have shown that non-probability samples can bias the estimates (Allcott, 2015; Tipton & Olsen, 2018; Yeager et al., 2019).

³ For detailed information on the intervention procedure and data collection, see pre-registration

Research Questions

The growth mindset treatment delivers the message that a student can change her belief in her ability to learn, especially when she faces challenges. If the treated student successfully internalizes this message, she is more likely to increase her level of effort, which can have a positive effect on her academic outcomes. As the treatment effect was expected to vary by school context and individual mindset, we examined the following research questions:

1. To what extent did the intervention change math course-taking patterns, such as course enrollment and GPA, and did these changes vary by subgroup, especially for low-income students and students of color?
2. Did the growth mindset treatment effects on math course-taking vary by pertinent school-level or student-level factors?

Data

Sample

This study leveraged data from the NSLM, a randomized controlled trial of a growth mindset program in the U.S. in K–12 settings, in which a brief online growth mindset program was administered to 9th-grade students during the 2015–2016 academic year. The NSLM features a nationally representative probability sample of regular U.S. public high schools.⁴ Over 12,000 public schools were stratified by their achievement level and fraction of racial minority students. Among 139 randomly selected schools, over 16,000 students from 76 schools participated in the intervention. Of the 76 schools, 11 did not provide administrative and transcript data and were excluded in the analysis.⁵ The final analytical sample therefore included 13,660 students from 65 high schools.

Study design

The NSLM was specifically designed to understand which kinds of 9th-grade students, in which kinds of classrooms and in which kinds of schools, are most likely to benefit from the growth mindset program. In the NSLM, students were randomly assigned to complete either the growth mindset program (treatment group) or a control activity during two 25-minute sessions. In the growth mindset program, students read and listened to materials describing scientific evidence about how the brain works and why people can grow their intellectual abilities over time. The program encouraged students to think about why they might want to grow their brain in order to make a difference on something that matters to them, such as their family, community, or a social issue they care about.

Key measures

(<https://osf.io/r82dw/>).

⁴ “Regular high schools” excludes charter and private schools, schools with specialized missions or populations, schools with 25 or fewer 9th-graders, and schools for which 9th grade is not the lowest grade. These regular public high schools serve more than 80% of the 9th-graders in the U.S.

⁵ For more information on the sample of schools, see Yeager et al. (2019) and Gopalan and Tipton (2018).

We created scale scores for pre-treatment growth mindset questions. During the first session, students answered three items about their mindset on a 6-point scale prior to random assignment.⁶ The pre-mindset measure is the sum of the mean raw scores of these three items on mindset, where a larger score indicates a fixed mindset. During the second session, students answered the same questions. Similarly, we constructed a post-mindset measure by averaging the raw scores from these three questions.⁷

The NSLM administered a behavioral challenge-seeking task at the end of the second session, in which students were asked to create worksheets with easy problems and hard problems. Hard problems may be challenging but can help students learn a great deal; as such, the task was designed to measure students' willingness to take on a challenging but potentially rewarding school assignment, which would not necessarily be subject to reference bias. We used the difference between the number of hard items and the number of easy items selected.⁸

The NSLM data provided end-of-school-year GPA for 8th- and 9th-graders, and detailed course information for math, science, social studies, and English/Language Arts courses. For schools that delivered the intervention in the fall of 2015, end-of-school GPA was the average of fall 2015 and spring 2016 grades; for schools that delivered the intervention in the spring of 2016, end-of-school GPA was comprised of spring 2016 grades.

This study used the course titles of and assigned a course intensity level to each course, similar to the categories employed in Riegle-Crumb (2006) and Kim et al. (2019). The categories are: 1—Basic or General Math; 2— Pre-Algebra; 3—Algebra I; 4—Geometry; 5—Algebra II; 6—Advanced Math (Algebra III, Trigonometry, Statistics, and Probability); 7—Pre-Calculus; 8—Calculus; and 9—Advanced Placement (AP) courses.

Additionally, we retrieved individual demographic information (gender, race, special education, English Language Learner, gifted program, repeating 9th grade, and free/reduced-priced lunch), mother's education, other survey information (expected grade and survey complete status), and 8th-grade math GPA.

Descriptive statistics

Table 1 reports the sample means and balance tests. Approximately 40% of the sample were female; 43% were White; 7% were in special education; and 27% were eligible for free or reduced-priced lunch. Panel A shows that the treatment and control groups were balanced along demographic characteristics. One exception, however, is that mother's education was higher for

⁶ Students answered the following three questions, where 1 corresponds to strongly disagree and 6 to strongly agree: 1) You have a certain amount of intelligence, and you really can't do much to change it; 2) Your intelligence is something about you that you can't change very much; and 3) Being a "math person" or not is something that you really can't change. Some people are good at math and other people aren't. The reliability (internal consistency) measured by Cronbach's alpha is 0.7243.

⁷ These self-reported measures may suffer from a reference bias in making between-school comparisons (e.g., Duckworth & Yeager, 2015). The literature on reference bias suggests that the differences in self-reports over time or across students may reflect differences in normative standards rather than authentic differences in skills (West et al., 2018), or they may reflect cultural differences in the school environment that lead students to interpret items in different ways. However, West et al. (2018) have shown that the reference bias may be minimal regarding growth mindset.

⁸ For details regarding the challenge-seeking worksheet task, see <https://osf.io/byc2e/>.

students in the control group. Panel B indicates that there was no difference in terms of math course-taking in 9th grade, further indicating that the randomization was successful.

The majority (77%) of students received the intervention in the fall, but pre-mindset score was comparable between the two groups. Mindset scores for control group students remained stable between the two sessions, whereas the score for students in the treatment group decreased by 0.5 points, equivalent to 0.47 standard deviations. In other words, students who received the treatment developed more of a growth mindset.

Next, we examined whether students' gender, socioeconomic status (SES), and racial and ethnic differences were related to their mindset. We used the key demographic variables and mindset scores measured prior to the random assignment. Relative to male students, female students' pre-mindset scores were 0.065 points higher, indicating that they had relatively fixed mindsets. Given that the difference was equivalent to 0.06 standard deviations, the effect size is not economically meaningful.

The next panel presents SES differences in mindset. Results show that students receiving special education or identified as an English Learner or eligible for free or reduced-priced lunch reported lower levels of growth mindset. The differences ranged from 0.275 to 0.533 points, equivalent to 0.22 to 0.47 standard deviations, and are were statistically significant. On the other hand, students in the gifted or talented education program or whose mothers earned a college degree had higher levels of growth mindset. In sum, the differences in pre-mindset favored students from advantaged backgrounds.

Finally, Panel C reports the racial and ethnic differences in growth mindset compared to White students. African-American students reported lower levels of growth mindset, whereas Asian students reported higher levels of mindset than White peers. Hispanic students reported slightly lower levels of mindset (roughly 0.09 standard deviations).

Overall, girls in 9th grade reported a slightly more fixed mindset than boys, and students from advantaged backgrounds reported higher levels of growth mindset. Regarding racial and ethnic differences, it is not clear whether minority students reported higher or lower levels of growth mindset. We now turn to our results regarding 1) the estimates of the causal effects of the randomized growth mindset intervention on math course-taking, and 2) the extent to which the intervention was successful in closing racial/ethnic and economic gaps in course-taking.

Empirical strategy

To examine the impact of the growth mindset treatment on course-taking in 9th grade, we used the following model:

$$Y_{is} = \beta_0 + \beta_1 Mind_i + \beta_2 X_i + \mu_s + \epsilon_{is}$$

where Y_{is} represents the course-taking outcomes in 9th grade described below and $Mind_i$ is an indicator of whether student i is treated with the growth mindset intervention. X_i is a vector of

individual-level covariates⁹ and μ_s captures the school fixed effects.¹⁰ Standard errors were clustered at the school level.

The main parameter of interest here is β_1 , which represents the estimated effect of the growth mindset treatment. Using this general model, we investigated whether mindset-treated students differed from their control group peers on key outcomes: namely, course-taking variables including course enrollment and grades. Since the average treatment effects on course-taking were expected to be small, it was important to investigate the heterogeneity of treatment effects across schools and contexts. Specifically, we conducted subgroup analyses and examined the extent to which school resources and context were related to the success of the intervention.

In addition, we measured the changes in growth mindset scores after treatment and compared variations in course-taking patterns and outcomes between students who experienced high growth and those with low growth in mindset. We were particularly interested in the extent to which an improved growth mindset could help students succeed in a course, and when the differences in outcomes would appear.

Results

Mindset and course enrollment in 9th grade

Before we estimated the causal effects of the growth mindset treatment on math course-taking outcomes, we explored how mindset predicts initial math course-taking choices in 9th grade.¹¹ Results in Appendix Table 1 indicate that, although correlational, students completing higher levels of math in 9th grade had more of a growth mindset. For example, the pre-mindset score for students whose highest level of math in 9th grade was Basic or General Math was 3.44. The scores continue as follows, according to highest level of math completed in 9th grade: 3.38 for Pre-Algebra; 3.11 for Algebra I; 2.76 for Geometry; and 2.68 for Algebra II or more advanced math courses.

Next, we regressed the highest level of math taken in 9th grade on pre-treatment mindset scores, the highest level of math completed by 8th grade, individual demographic variables, and school dummy variables. Column 1 shows that the estimated coefficient on pre-mindset scores was -0.017, which was statistically significant at the 1% level. The negative estimated coefficient indicates that, although correlational, students who had more of a growth mindset had taken higher levels of math in 9th grade, while the effect size was not practically large. Column 2 additionally controls for the treatment indicator. Because the intervention was conducted after the fall semester had begun, math course enrollment, which was determined prior to the intervention, should not have been affected by the treatment. Controlling for the treatment indicator did not change any estimated coefficients and the estimated coefficient on the treatment

⁹ X includes student demographics (race dummies with White as the reference group, gender dummy, pre-treatment expectation measures, a function of within-school math GPA in 8th grade, parental education, indicator for English Language Learner classification, indicator for gifted and talented status, indicator for special education classification, indicator for free or reduced-price lunch, indicator for repeating 9th grade, and indicators for missing key variables), survey characteristics (indicator for completing the survey in each session, and expected grade), and 8th-grade GPA.

¹⁰ Restricting the comparisons within the same school minimizes the possibility of reference bias in self-reported measures (Blazar & Kraft, 2017).

¹¹ For the correlational relationship between mindset and SES, Destin et al. (2019) used NSLM data focusing on control group students and showed that higher SES is associated with fewer fixed beliefs about academic ability.

indicator was not statistically significant, suggesting that the treatment did not predict math course-taking in 9th grade.

Next, we examined whether advancing to the next level of math in 9th grade was related to the students' mindset. Column 3 restricts the sample to those whose highest level of math in 8th grade was Pre-Algebra and shows that students with more of a growth mindset were marginally more likely to proceed with the next level of math, Algebra I, in 9th grade. Column 4 focuses on students whose highest level of math in 8th grade was Algebra I, testing whether they were more likely to take the next level course, Geometry, in 9th grade. Results indicate that students with stronger self-reported growth mindset were more likely to move up to Geometry in 9th grade after taking Algebra I in 8th grade.

In sum, self-reported growth mindset was positively related to advanced math course enrollment and likelihood of on-time progression through math course levels.¹²

Mindset Treatment and Post-Survey Outcomes

Here, we examined the treatment effects on student self-reported mindset and challenge-seeking behaviors from the second-session survey. Post-survey mindset scores were the mean of the raw scores of the three mindset questions, and challenge-seeking behavior was the difference between the number of hard questions and the number of easy questions selected. Estimated treatment effects are summarized in Table 3, where each column includes individual covariates and school fixed effects. The average student in the control group answered 2.902 to the post-mindset questions and the treatment effect on self-reported mindset was -0.381, which is significant at the 1% level. Students who were assigned to a growth mindset treatment reported more of a growth mindset than control group students.

In column 2, we report the treatment effects on challenge-seeking behavior. The expectation was that students who received mindset treatments would consider challenges as learning opportunities and that these students would be more likely to choose harder questions than control group students. The average student in the control group reported having chosen one fewer hard question than they did easy math questions. The treatment appears to have had positive effects on challenge-seeking behavior, leading treated students to choose more challenging math questions.

In sum, using both self-reported score and behavior task activities, there was clear evidence of mindset treatment effects. Results on heterogeneous treatment effects, summarized in Appendix Table 2, indicate that the students from advantaged backgrounds were more likely to have more of a growth mindset and choose more challenging questions.

Next, we proceeded to study the causal effects of the growth mindset program on math GPA, to gain a more complete picture of the relationship between growth mindset and math performance.

¹² We also investigated whether any covariates predicted the pre-mindset scores. Correlational results indicate that a student was more likely to have more of a growth mindset if he was Asian, attended a school that received the intervention during the fall semester, and took more advanced math in 8th or 9th grade. On the contrary, a student who was female, received special education, or had less proficiency in English was more likely to have a fixed mindset (results not reported).

Mindset effects on GPA

In Table 4, we show the results of our estimated mindset treatment effects on course GPA (as measured at the end of the school year). Columns 1 and 2 report the estimated treatments on overall GPA, with and without control variables, respectively. Column 1 shows that the mindset treatment increased GPA by 0.007 and was not statistically significant. Note that treatment group students had a lower 8th-grade GPA and a smaller fraction of them were in gifted or IB programs. Adding individual covariates increased the effect to 0.03 GPA points and was statistically significant at the 1% level. Column 2 also shows that the standard errors decreased by 39%. The difference in estimated coefficients along with the balance test in Table 1 indicate that additional control variables corrected for the bias that randomization did not fully account for. Columns 3–6 present the estimated treatment effects on GPA by subject. The treatment effects were positive and significant for math, science, and STEM courses (between 0.037 and 0.043), whereas the effects were smaller and insignificant for English and social science courses (0.018 and 0.012, respectively). The effect size for math GPA was 0.03 standard deviations. To invalidate the inference of an effect of the mindset program on math GPA, bias must account for 15% of the estimated effect and we would need to replace 15% (about 1,760 pairs) of students with other students for whom there were no treatment effect (Frank, Maroulis, Duong, & Kelcey, 2013). Given the fact that we estimated the effects using an RCT in a representative sample, we would have retained our inference.¹³

Results in Table 4 report the mindset treatment effects averaged across all students. As the treatment may have had different effects based on individual characteristics, we examined the heterogeneous treatment effects, focusing on overall and math GPA. Table 5 summarizes the treatment effects by subgroups. There is no evidence that the treatment increased GPA differently across genders. On the other hand, Panel B shows that the GPA improved among students whose mothers received a college or more advanced degree. Panel C provides similar results in that the treatment increased the GPA for White students. Additional analyses in which the treatment indicator is interacted with racial dummies show that the treatment had a larger effect on overall 9th-grade GPA for White students relative to the control group students than for African-American students.

Mindset effects on GPA by math course's level of rigor

Results in Table 4 indicate that after the brief intervention, student math GPA increased by an average of 0.05 grade points on a 4.3-point metric. Here, we examined the extent to which the mindset treatment effects differed by level of rigor of 9th-grade math courses. Estimated coefficients in Table 6 show that the treatment effects were positive and significant for students taking Geometry or Algebra II courses in 9th grade, whose self-reported growth mindset was positively correlated with advanced course-taking (Appendix Table 1). On the other hand, the effects were smaller and insignificant for lower-level courses, including Pre-Algebra and Algebra I. Results indicate that the mindset treatment

¹³ As post-treatment GPA was the average of 9th-grade fall and spring GPAs for those who completed surveys in the fall semester, we further examined whether the timing of treatment is related to the treatment effect sizes. We tested whether the treatment was more effective during the treatment semester or whether the effect size became larger in the subsequent semester. Results indicate that the post-treatment math GPAs were similar regardless of the treatment timing (results not reported).

was more effective among students taking more advanced courses and minimal for those taking the lower-level courses.

Mindset effects for Algebra I-takers

Although we did not find mindset effects on math GPA for Algebra I-takers, the benefit of the treatment might have accrued differently depending on a student's math ability. For example, treatment effects on math GPA were larger among advanced students taking Geometry or Algebra II in 9th grade and among relatively high-achieving students taking Algebra I in 9th grade. Thus, we restricted the sample to students who took Algebra I in 9th grade. These students were considered on track to complete Algebra II or Pre-Calculus by the end of high school, courses that are generally considered the threshold for college admission (Adelman, 1999).¹⁴

We calculated quartiles within each math class by 8th-grade math test scores and estimated the treatment effects separately by these quartiles.¹⁵ Results in Table 7 show that the estimated coefficients were largest and statistically significant among the most prepared students. Results in Columns 2–4 indicate that the mindset treatment did not appear to help improve the GPA of students with a lower 8th-grade math GPA taking Algebra I.

These results should be considered alongside previous findings that the mindset treatment was more effective for lower-achieving students: for example, Yeager et al. (2019), using the same NSLM data, found that the mindset treatment improved grades among lower-achieving students and increased overall enrollment in advanced math courses. However, it is important to note that Yeager et al. defined lower achievement differently. They assigned students with an 8th-grade GPA at or below the school-specific median in the term preceding the random assignment as lower-achieving, whereas we defined achievement level according to students' math ability within each math class (students with an 8th-grade math GPA in the lowest quintile were defined as lower-achieving). In addition, 9th-grade Algebra I enrollees generally include many relatively low-achieving students. As 70% of students take Algebra I in 9th grade, Algebra I-takers are a more generic sample. In addition, students who take Algebra II in 10th grade are generally high-achieving students. Thus, these two findings are not necessarily in conflict.

School context

In this section, we explore how school context related to the program's effectiveness.

Pre-mindset scores

We measured the average school pre-mindset scores and calculated school-level quartiles. The first quartile included schools in which students reported already having strong growth mindsets and fourth-quartile schools reported students having strong fixed mindsets

¹⁴ According to course intensity category outlined in the previous section, basic or general math and Pre-Algebra in 9th grade were considered as lower-level math courses, whereas Geometry and Algebra II or more advanced courses were referred to as “advanced track,” in terms of college preparation.

¹⁵ We created additional sample restrictions to generate reasonable quartile measures. In particular, we dropped schools in which the number of students taking math courses in 9th grade were fewer than 40.

before the growth mindset program was implemented. As the scores for the 2nd and 3rd quartiles were similar to each other (Online Appendix Figure 1), we merged these two quartiles into a group. Results were similar when we divided the sample into quintiles and merged the center quintiles.

Results in Table 8 show non-linear treatment effects on average GPA by school context, which was measured by mindset scores prior to the intervention.¹⁶ Estimates indicate that the mindset treatment was more effective for 2nd- and 3rd-quartile schools. For example, the benefit of the mindset treatment for students in 2nd- and 3rd-quartile schools was 0.039 (standard error of 0.021), which was statistically significant at a 10% confidence level, whereas that of 1st-quartile schools was 0.002 (standard error of 0.023).¹⁷ It is notable that we failed to detect any treatment effects for students in 1st-quartile schools. In other words, the treatment was effective for students from schools at the middle of the pre-mindset distribution who had more chances to move, but not from schools at the extreme points (such as those with a fixed mindset or those already demonstrating a growth mindset).¹⁸

Changes in mindset for control group students

Another school characteristic that we tried to measure for the school context was the fraction of control group students who did not participate in the growth mindset program but nevertheless experienced an increase in self-reported growth mindset. The hypothesis behind this measure was that, because students were surveyed in 9th grade, when the vast majority of students are attending a new school, an increase of growth mindset among control group students could be related to many factors: these include being immersed in a school context that emphasizes and supports the development of a growth mindset, certain pedagogical or curricular approaches, or being surrounded by peers who support growth mindsets.¹⁹

The school average of pre-mindset scores might have been correlated with other school characteristics predicting students' academic outcomes. Since these pre-mindset scores were determined prior to the intervention, they cannot measure what happened at the school after the intervention. This fraction measurement, on the other hand, is more suitable to measuring school-specific developmental contexts that were not affected by mindset treatment.

¹⁶ In the analysis, we excluded schools that received interventions in the spring semester because the pre-mindset scores were likely to be changed compared to the ones measured in the fall semester. In addition, spring schools have a larger proportion of students taking lower-level math courses both in 8th and 9th grade compared to fall schools. Students attending "spring" schools may have different individual characteristics that are correlated with GPA than those attending "fall" schools. The latter issue can be partly resolved by controlling for a rich set of individual characteristics.

¹⁷ We calculated the benefit for students from a specific quartile from the full specification, which is

$$Y_{is} = \tau_0 + \tau_1 \text{Mind}_i + \tau_2 \text{Pre1} + \tau_3 \text{Pre2} + \tau_4 \text{Mind}_i \times \text{Pre1} + \tau_5 \text{Mind}_i \times \text{Pre2} + \tau_6 \mathbf{X}_i + \mu_s + \epsilon_{is}.$$

For example, the benefit of the mindset for students in 2nd- and 3rd-quartile schools equals $\tau_1 + \tau_2$.

¹⁸ We experimented with the analyses using other specifications and found that, for example, adding school measures or interactions did not change the main estimates, and interactions were not significant.

¹⁹ This measure includes the interaction between control group students and treated students. As long as the interaction does not differ by school observables, it will not affect the ordering. Guillaume (2019) has examined the existence of peer effects (or spillovers) for the growth mindset intervention using the NLSM data. Note that there may be cross-contamination factors that can plague all these types of within-school programs.

However, this measurement is not only a function of school context but also a function of initial mindset scores, which means that schools with higher pre-mindset scores would likely have fewer changes in mindset. To distinguish school context measures unrelated to school pre-mindset measures, we divided the schools into nine categories based on their pre-mindset scores and changes in fraction of students toward a growth mindset; we then generated subgroup estimates of the mindset effect to the school context and identified the subgroups that were affected by the treatment.²⁰

There were two to four weeks between the sessions, and the extent to which the school context fostered mindset was likely to differ across schools. As such, we focused on schools that received treatment in the fall semester, as students had spent only a few weeks in the school. We exclude schools that had sessions in the spring semester, as 9th-graders in these schools had already spent a semester in high school and thus their mindset was already affected by other school characteristics.²¹

Results in Table 9 indicate that schools with a larger fraction of students who moved toward a growth mindset had a higher GPA, indicating that the growth mindset treatment was more effective if the school environment was more growth-mindset-friendly,²² which is consistent with Yeager et al. (2019).²³ Consistent with findings in Table 8, we observed no significant treatment effects among schools that had “already growth” mindsets (columns 1–3) or fixed mindsets (columns 7–9). However, though not significant, the estimates were larger for schools in a growth-mindset-friendly environment.

Taken together, results indicate that at schools where a larger fraction of control students showed increases in growth mindset *without* participating in the growth mindset program, students who *did* participate in the program showed above-average GPA improvement—a finding that requires further investigation of other factors that may enhance the effects of growth mindset programs.

Individual context

Finally, we examined whether students who had the largest change in growth mindset had different course-taking patterns and achievement compared to peers with smaller changes in growth mindset. We did so by measuring the changes in mindset scores between sessions and focused on treated students. We added the changes in mindset score variables to

²⁰ Another way to measure school context is to use teacher surveys on mindset, which include questions targeting teachers’ general intelligence mindsets (i.e., teachers’ beliefs about whether intelligence, in general, is fixed or malleable) and math-specific intelligence mindsets (i.e., teachers’ beliefs about whether math ability is fixed or malleable). However, the data only provide teacher information among math teachers, with a response rate of 23%, which is too limited to fully capture the school context.

²¹ We realize that, by doing so, we could no longer generalize the results to the national sample; however, this limitation was of little relevance in the context of the present study, as we were interested in whether school context matters for treatment effectiveness.

²² Alternatively, schools with larger changes may be better schools with students with higher GPAs, where the mindset treatment may have worked better. Either way, the measure captures a contextual factor regarding mindset growth.

²³ Yeager et al. (2019) used challenge-seeking task values to measure peer norms that support the growth mindset belief system. The authors found that the GPA for lower-achieving 9th-graders improved more when students were surrounded by more supportive peers.

the main specification in Equation (1). Results in Table 10 show that the mindset treatment interacted with changes in mindset. The coefficient on the changes in mindset scores in column 2 indicates that the mindset treatment increased GPA by 0.054 points for students who changed 1 point toward a growth mindset. Given that the average change in mindset score was 0.5, the estimate indicates a treatment effect of 0.03. The estimate is close to the main effect size in Table 4, implying that the mindset treatment effect was linked to changes in individual mindset, controlling for pre-mindset and other individual characteristics. Note that the pre-mindset score was balanced between treatment and control group students.²⁴ To examine whether a non-linear relationship exists, we divided the sample into quintiles based on the changes in mindset scores. Results in columns 3–7 indicate that the treatment effect on GPA was particularly large among the most fixed-mindset students, who on average changed 1.041 points toward a growth mindset.

We acknowledge that the estimates using the changes in mindset score are not a perfect measure for the treatment mechanism, but we offer preliminary evidence of a mediated effect linked to changes in individual mindset. In particular, the mindset treatment was effective for changing students' mindset, and students who changed more toward a growth mindset had higher treatment effects in terms of their GPA.²⁵ Future analysis using standardized test scores will be helpful in determining whether the treatment creates student behavioral changes that teachers can subjectively observe.

Discussion

This study suggests that the growth mindset intervention was modestly effective in terms of GPA improvement for students who were taking advanced math courses and who had a higher incoming math GPA, which extends findings from previous studies showing that growth mindset predicts an increase in GPA in high school (e.g., Blackwell, Trzesniewski, & Dweck, 2007). Results on heterogeneous treatment effects suggest that the likelihood of the mindset treatment being equally beneficial to all students is quite low. In a higher education context, studies have shown that the mindset treatment improved academic outcomes and degree completion for a sub-population of the target group, e.g., Pell-eligible or Latinx students (Broda et al., 2018; John et al., 2019; Kim et al., 2020). As social and emotional learning measures are malleable and predict long-term outcomes, it may be important to identify a key group of students who are likely to be most receptive to the treatment.

Findings indicate that school context around growth mindset is related to the success of the intervention. This suggests that schools and policymakers may think about enhancing

²⁴ In a different sample specification, we included all control group students and additionally controlled for the interaction of the mindset treatment and changes in mindset scores. When the changes in mindset score variable were added, the coefficient on mindset dropped from 0.027 to 0.014 and became statistically insignificant. Next, we added the interaction variable and the coefficient on the interaction was -0.038 (standard error of 0.014). The coefficient on pre-mindset score did not change, indicating that there was no correlation between pre-mindset and mindset interaction effects. Adding interaction terms also did not change the coefficients of other demographic variables.

²⁵ Alternatively, causal inference methods can be used for mediation analysis to examine the relationship. For example, the endorsement of the belief that intelligence is malleable may have a positive effect on GPA and future course-taking. See VanderWeele (2015) for a discussion.

students' growth mindset through improving the learning environment and school norms as a whole, which may amplify the positive effects of interventions specifically targeted at developing growth mindsets. Since the findings can be generalized to diverse groups, results are expected to provide practical policy implications for schools and teachers: teachers and schools can target student populations to improve their growth mindsets, which could lead to more pro-academic course-taking patterns and better outcomes.²⁶ Moreover, as teachers are shown to have impacts on non-achievement outcomes, such as self-reported self-efficacy (Blazar & Kraft, 2017), on-time high school graduation (Jackson, 2018), and absences (Liu & Loeb, 2020), schools and teachers can also identify professional development plans or strategies to help develop these non-achievement skills among their students.

One such strategy involves low-cost educational interventions, which have recently been shown by a number of studies to be effective in helping students take relatively simple one-time actions (Lazowski & Hulleman, 2016; Oreopoulos et al., 2018). Unlike these light-touch interventions, such as sending text messages to help students renew financial aid (Castleman & Page, 2016), the nudge message used in the growth mindset intervention is an invitation for students to work harder over time, which requires substantial and sustained changes in their behavior. This study offers evidence that the message to work harder is more effective for students who are more likely to have worked hard previously and experienced the benefit of doing so.²⁷ Thus, the expected payoff related to the idea of hard work may not be clear to some students, as it is not a clear long-term goal with high certainty. Schools can help increase students' awareness of the long-term benefits of hard work, and decrease uncertainty regarding these benefits—which may include improvement in their grades, college enrollment, and choice of major. For example, schools can provide examples of the kinds of benefits students might experience in the next semester or year through hard work. By showing the path to success, schools can increase students' motivation to engage in this process while lowering their uncertainty cost.

Recently, many states started to include non-academic measures as a new school accountability metric, especially under the Every Student Succeeds Act (ESSA), which requires states to include at least one measure of school quality or student success in their accountability systems (e.g. Grant et al., 2017). For example, 36 states and the District of Columbia chose to include attendance or chronic absenteeism measure in their accountability plans.²⁸ Also there is a growing interest in measuring social and emotional learning measures among state and district leaders. Although the current study provides causal evidence that the mindset treatment intervention can change students to more of a growth mindset and improve their short-run academic outcomes, incorporating these social and emotional learning measures into high-stakes programs must be approached with caution. It is well known that self-reported surveys are subject to reference bias (e.g., Duckworth & Yeager, 2015), social desirability bias (e.g., Paulhus, 1991), incentives and administrative conditions (e.g., Chen, Feng, Heckman, & Kautz,

²⁶ As more data become available, we will use course-taking information from subsequent years to estimate whether the mindset program helped students stay on-track in terms of college trajectories and whether it led to more pro-academic course-taking patterns and better outcomes. Current data provide the intended course enrollment information in 10th grade, but we could not find any intervention effects on the intended math course levels.

²⁷ Note that growth mindset is not simply about working harder, but involves learning effective strategies and asking for help. In addition, we acknowledge that there are other factors influencing placement in advanced course-taking, such as racial tracking (Kim, 2018).

²⁸ https://nces.ed.gov/programs/statereform/tab1_13.asp

2020), and measurement error (Gillen, Snowberg, & Yariv, 2019). Regarding the latter, in particular, Bertrand and Mullainathan (2001) have voiced concern around attempts to use survey data as dependent variables.

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Table 1. Sample means of NSLM 9th-grade cohort

	Overall	Control	Mindset	Difference (3)-(2)	p value (4)=0
	(1)	(2)	(3)	(4)	(5)
A. Demographics					
Female	0.394	0.390	0.397	0.007	0.413
White	0.430	0.431	0.428	-0.003	0.758
Asian	0.030	0.030	0.030	0.001	0.934
African American	0.120	0.118	0.122	0.003	0.537
Hispanic	0.192	0.193	0.191	-0.002	0.799
Other race	0.050	0.051	0.048	-0.003	0.378
Special education	0.068	0.07	0.066	-0.004	0.305
English Language Learner	0.032	0.034	0.031	-0.002	0.422
Gifted or IB	0.062	0.065	0.058	-0.007	0.093
Free or reduced-priced lunch	0.269	0.267	0.272	0.005	0.522
Mother's education	0.510	0.523	0.497	-0.026	0.003
B. Math course-taking in 9 th grade					
Took Basic or General Math	0.051	0.053	0.052	0.001	0.771
Took Pre-Algebra	0.098	0.100	0.099	0.002	0.743
Took Algebra I	0.625	0.614	0.619	-0.011	0.226
Took Geometry	0.184	0.189	0.187	0.005	0.492
Took Algebra II	0.039	0.042	0.040	0.003	0.427
Took Algebra III	0.001	0.001	0.001	0.000	0.751
Took Pre-Calculus	0.001	0.001	0.001	0.000	0.575
Took Calculus	0.001	0.001	0.001	0.000	0.558
C. Survey					
Completed session 1	0.866	0.889	0.843	-0.046	0.001
Completed session 2	0.722	0.721	0.722	0.001	0.944
Expected grade	4.041	4.048	4.034	-0.015	0.361
Received treatment in fall	0.768	0.770	0.765	-0.005	0.456
Pre-mindset score	3.059	3.066	3.052	-0.014	0.482
Post-mindset score	2.706	2.902	2.508	-0.394	0.000
D. GPA					
9 th GPA Total	2.592	2.6	2.596	0.007	0.700
9 th GPA Math	2.445	2.466	2.455	0.021	0.354
9 th GPA English	2.641	2.640	2.641	0.001	0.983
9 th GPA Social Studies	2.806	2.812	2.809	0.006	0.789
9 th GPA Science	2.568	2.596	2.582	0.028	0.207
9 th GPA STEM	2.502	2.526	2.514	0.024	0.253
8 th GPA	0.045	0.060	0.030	-0.030	0.044
Observation	13,660	6,836	6,824	13,660	

Table 2. Summary statistics for mindset scores

	Mindset	Mindset for Reference Group	Difference (1)-(2)	p value (4)=0	Effect size
	(1)	(2)	(3)	(4)	(5)
A. Gender Differences					
Female	3.073	3.007	0.065	0.003	0.057
B. SES Differences					
Special education	3.466	2.933	0.533	0.001	0.466
English Language Learner	3.347	3.038	0.309	0.001	0.246
Free or reduced-priced lunch	3.171	2.896	0.275	0.001	0.228
Mother's education—college	2.929	3.208	-0.279	0.001	-0.249
Gifted or IB	2.755	3.031	-0.276	0.001	-0.250
C. Racial and Ethnic Differences					
African American	3.284	2.963	0.001	0.001	0.251
Hispanic	3.063	2.963	0.001	0.001	-0.086
Asian	2.714	2.963	0.001	0.001	-0.222

Notes: The mindset measure is the sum of the mean raw scores of three pre-mindset questions, where a larger score indicates a fixed mindset. Column 1 reports the pre-mindset scores for the corresponding group. Column 2 reports the average pre-mindset scores for the corresponding reference group. For example, the reference group for female is male and the reference group for special education is a group of students not taking special education. The reference group in Panel C is White. Column 3 reports the difference in mindset scores and column 4 presents its p value, where the null hypothesis is that the difference is equal to zero. Column 5 presents the effect size, which is the fraction of the difference in column 3 and standard deviations of corresponding group's mindset scores.

Table 3. Estimated effects of mindset on post-treatment survey outcomes

	Post-mindset (1)	Challenge-seeking (2)
Mindset	-0.381*** (0.017)	0.865*** (0.068)
Control Mean	2.902	-1.086
Observation	12,130	8,490

Notes: Post-mindset is the mean of raw scores of three mindset questions measured in the second session. A larger score indicates a fixed mindset. Challenge-seeking is the difference between the number of hard questions and the number of easy questions selected. Each column includes controls for demographic characteristics, prior achievement scores, pre-treatment mindset scores, and school fixed effects. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Estimated effects of growth mindset treatment on 9th-grade GPA

	GPA (1)	GPA (2)	GPA (3)	GPA (4)	GPA (5)	GPA (6)	GPA (7)
Mindset	0.007 (0.018)	0.030** (0.011)	0.037* (0.016)	0.018 (0.014)	0.012 (0.016)	0.043** (0.015)	0.041** (0.013)
Pre-mindset		-0.034*** (0.005)	-0.022** (0.008)	-0.032*** (0.007)	-0.043*** (0.008)	-0.044*** (0.007)	-0.034*** (0.006)
8 th -grade GPA		0.552*** (0.010)	0.576*** (0.013)	0.523*** (0.012)	0.511*** (0.014)	0.564*** (0.013)	0.567*** (0.011)
Subject	All	All	Math	English	Social Studies	Science	STEM
Covariates	No	Yes	Yes	Yes	Yes	Yes	Yes
Observation	12,490	12,490	11,540	12,050	9,900	11,590	12,090

Notes: Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects. Column 1 does not include any covariates. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Estimated effects of growth mindset treatment on 9th-grade GPA by subgroup

	Overall GPA		Math GPA	
	Mean of Control Group	Treatment Effects	Mean of Control Group	Treatment Effects
Full Sample	2.592	0.030** (0.011)	2.445	0.037* (0.016)
A. Gender Differences				
Male	2.451	0.029+ (0.015)	2.316	0.033 (0.021)
Female	2.794	0.034+ (0.017)	2.631	0.042+ (0.025)
B. SES Differences				
Special education	2.004	-0.026 (0.049)	1.969	-0.121+ (0.068)
English Language Learner	2.07	-0.083 (0.082)	1.937	-0.081 (0.113)
Free or reduced-priced lunch	2.211	0.011 (0.023)	2.084	0.009 (0.035)
Mother's education—college	2.883	0.031* (0.014)	2.724	0.040+ (0.021)
Gifted or IB	3.295	0.045 (0.036)	3.111	0.058 (0.050)
C. Racial and Ethnic Differences				
White	2.758	0.053** (0.016)	2.586	0.057* (0.023)
African American	2.077	-0.007 (0.034)	1.918	0.036 (0.054)
Hispanic	2.345	0.006 (0.026)	2.18	-0.004 (0.038)
Asian	3.314	-0.004 (0.052)	3.178	0.091 (0.086)

Notes: Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects, for each subgroup. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6. Estimated effects of growth mindset treatment on 9th-grade math GPA by math level

	Basic Math	Pre-Algebra	Algebra I	Geometry	Algebra II	Algebra III or Advanced
	(1)	(2)	(3)	(4)	(5)	(6)
Mindset	0.03 (0.081)	0.027 (0.054)	0.035 (0.023)	0.051 ⁺ (0.029)	0.109 ⁺ (0.066)	0.000 (0.000)
Observation	510	1,040	6,230	1,910	420	10

Notes: Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Estimated effects of growth mindset treatment for Algebra I-takers

	Baseline (1)	Q1 (2)	Q2 (3)	Q3 (4)	Q4 (5)
Mindset	0.037 (0.027)	0.021 (0.051)	0.075 (0.062)	-0.011 (0.047)	0.123* (0.058)
Observation	4,190	1,480	930	1,110	680

Notes: The outcome is 9th-grade math GPA in all columns. Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects. The sample was restricted to students who took Algebra I in 9th grade. We calculated quartiles within each math class by 8th-grade math test scores and estimated the treatment effects separately by these quartiles. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. Estimated effects of growth mindset treatment by school pre-mindset

	9 th GPA (1)	9 th GPA (2)	9 th GPA (3)
Mindset	0.029 (0.014)	0.021 (0.014)	0.036 (0.186)
School Pre-mind Q1		0.262*** (0.024)	0.266*** (0.030)
School Pre-mind Q2 Q3		0.221*** (0.022)	0.207*** (0.028)
Mind x Pre-mind Q1			-0.009 (0.036)
Mind x Pre-mind Q2Q3			0.028 (0.034)
Observation	9,620	9,620	9,620

Notes: The outcome is 9th-grade overall GPA in all columns. Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects. Column 2 includes indicators for school-level average of pre-mindset quartiles, where the 2nd and 3rd quartiles are merged and the 4th quartile is omitted. Column 3 additionally controls for the interaction of treatment and school pre-mindset quartiles. The sample excludes schools that received the treatment in the spring semester. Standard errors clustered by school are in parentheses.

⁺ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. Estimated effects of growth mindset treatment by school context

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Pre1	Pre1	Pre1	Pre2	Pre2	Pre2	Pre3	Pre3	Pre3
	Frac1	Frac2	Frac3	Frac1	Frac2	Frac3	Frac1	Frac2	Frac3
Mindset	-0.033 (0.052)	0.002 (0.027)	0.019 (0.062)	0.061 (0.041)	0.057* (0.027)	0.063+ (0.034)	-0.036 (0.090)	-0.036 (0.041)	0.050 (0.044)
N	280	2,150	250	1,200	2,180	1,330	250	900	1,080

Notes: The outcome is 9th-grade overall GPA in all columns. Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, school fixed effects, and school context variables measured by pre-mindset scores and the fraction of students who moved toward a growth mindset. The sample is divided into three groups by school-level pre-mindset scores and the fraction measure. Pre1 in columns 1–3 includes schools that have “already growth” mindsets. Pre3 in columns 7–9 includes schools that have fixed mindsets. Frac1 includes schools that have the smallest fraction of students who moved toward a growth mindset. Frac3 includes schools that have the largest fraction of students who moved toward a growth mindset. The sample excludes schools that received the treatment in the spring semester. Standard errors clustered by school are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. Estimated effects of growth mindset treatment by individual mindset scores

	(1) Baseline	(2) +Changes in Mindset	(3) Q1 Growth	(4) Q2	(5) Q3	(6) Q4	(7) Q5 Fixed
Premind	-0.026** (0.009)	-0.054*** (0.011)	- 0.093** (0.033)	-0.040 (0.025)	-0.052* (0.023)	-0.046* (0.021)	-0.031 (0.029)
Changes in Mindset		-0.060*** (0.011)	-0.062 (0.043)	-0.033 (0.094)	0.111 (0.134)	-0.143 (0.158)	-0.090* (0.046)
Mean Premind	3.043	3.042	3.943	3.245	2.599	2.631	2.612
Mean Changes in Mindset	-0.575	-0.575	-2.057	-0.960	-0.446	0.058	1.041
N	4,780	4,480	970	990	950	850	720

Notes: The outcome is 9th-grade overall GPA in all columns. Each estimate comes from a linear regression of GPA on demographic controls, prior achievement scores, pre-treatment mindset scores, and school fixed effects. Column 2 additionally controls for changes in individual mindset scores. Columns 3–7 provide estimates that were estimated separately by quintiles in changes in individual mindset scores. Column 3 reports the estimated treatment effects for 1st-quintile students, who experienced the largest change toward a growth mindset. The sample excludes control group students. Standard errors clustered by school are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Online Appendix Figure 1. School-average pre-mindset scores

Notes: Red lines indicate school-level quartiles for pre-mindset scores.

Appendix Table 1. Estimated effects of mindset on math course-taking in 9th grade

	Highest math taken (1)	Highest math taken (2)	Took Algebra I (3)	Took Geometry (4)
Pre-mindset	-0.017*** (0.005)	-0.017*** (0.005)	-0.006+ (0.003)	-0.021*** (0.006)
Mindset		0.005 (0.010)		
Observation	8,490	8,490	5,540	1,780

Notes: Highest level of math is 1—Basic or General Math; 2—Pre-Algebra; 3—Algebra I; 4—Geometry; 5—Algebra II or Advanced Math. All columns include demographics and survey measures described in Table 1. Column 3 restricts sample to those whose highest level of math in 8th grade is Pre-Algebra. Column 4 focuses on students whose highest level of math in 8th grade is Algebra I. Each column includes controls for demographic characteristics, prior achievement scores, pre-treatment mindset scores, and school fixed effects

Appendix Table 2. Estimated effects of mindset on post-treatment survey outcomes by subgroup

	Mindset Scores		Challenge-Seeking	
	Mean of Control Group	Treatment Effects	Mean of Control Group	Treatment Effects
Full Sample	2.902	-0.381*** (0.017)	-1.086	0.865*** (0.068)
A. Gender Differences				
Male	2.893	-0.353*** (0.023)	-0.942	0.871*** (0.088)
Female	2.916	-0.426*** (0.025)	-1.309	0.859*** (0.108)
B. SES Differences				
Special education	3.351	-0.134 (0.082)	-1.000	0.611* (0.265)
English Language Learner	3.223	-0.206 ⁺ (0.115)	-0.151	0.474 (0.360)
Free or reduced-priced lunch	2.996	-0.365*** (0.035)	-0.971	0.582*** (0.128)
Mother's education—college	2.784	-0.396*** (0.023)	-0.963	0.885*** (0.097)
Gifted or IB	2.651	-0.494*** (0.059)	-0.361	0.860** (0.309)
C. Racial and Ethnic Differences				
White	2.822	-0.378*** (0.025)	-1.329	1.017*** (0.105)
African American	3.106	-0.292*** (0.058)	-0.759	0.539** (0.196)
Hispanic	2.954	-0.417*** (0.040)	-0.829	0.721*** (0.151)
Asian	2.652	-0.424*** (0.096)	0.131	0.798 ⁺ (0.443)

Notes: Post-mindset is the mean of raw scores of three mindset questions measured in the second session. A larger score indicates a fixed mindset. Challenge-seeking is the difference between the number of hard questions and the number of easy questions selected.