Monographs of the Society for Research in Child Development
Ginger A. Moore, Editor

Mindset × Context: Schools, Classrooms, and the Unequal Translation of Expectations into Math Achievement

Jamie M. Carroll,[1] David S. Yeager,[2] Jenny Buontempo,[2] Cameron Hecht,[2] Andrei Cimpian,[3] Pratik Mhatre,[2] Chandra Muller,[2] and Robert Crosnoe[2]

Abstract When do adolescents' dreams of promising journeys through high school translate into academic success? This monograph reports the results of a collaborative effort among sociologists and psychologists to systematically examine the role of schools and classrooms in disrupting or facilitating the link between adolescents' expectations for success in math and their subsequent progress in the early high school math curriculum. Our primary focus was on gendered patterns of socioeconomic inequality in math and how they are tethered to the *school's peer culture* and to *students' perceptions of gender stereotyping in the classroom*.

To do this, this monograph advances Mindset × Context Theory. This orients research on educational equity to the reciprocal influence between students' psychological motivations and their school-based opportunities to enact those motivations. Mindset × Context Theory predicts that a student's mindset will be more strongly linked to developmental outcomes among groups of students who are at risk for poor outcomes, but only in a school or classroom context where there is sufficient need and support for the mindset. Our application of this theory centers on expectations for success in high school math as a foundational belief for students' math progress early in high school. We examine how this mindset varies across interpersonal and cultural dynamics in schools and classrooms. Following this perspective, we ask:

[1]Tulane University, [2]University of Texas at Austin, [3]New York University.
Corresponding author: Jamie M. Carroll, Tulane University, New Orleans, LA, email: jcarroll2@tulane.edu

Citation Information: Carroll, J. M., Yeager, D. S., Buontempo, J., Hecht, C., Cimpian, A., Mhatre, P., Muller, C., & Crosnoe, R. (2023). Mindset × Context: Schools, classrooms, and the unequal translation of expectations into math achievement. *Monographs of the Society for Research in Child Development*, *88*(2).

https://doi.org/10.1111/mono.12471

1. Which gender and socioeconomic *identity groups* showed the weakest or strongest links between expectations for success in math and progress through the math curriculum?
2. How did the *school's peer culture* shape the links between student expectations for success in math and math progress across gender and socioeconomic identity groups?
3. How did *perceptions of classroom gender stereotyping* shape the links between student expectations for success in math and math progress across gender and socioeconomic identity groups?

We used nationally representative data from about 10,000 U.S. public school 9th graders in the National Study of Learning Mindsets (NSLM) collected in 2015–2016—the most recent, national, longitudinal study of adolescents' mindsets in U.S. public schools. The sample was representative with respect to a large number of observable characteristics, such as gender, race, ethnicity, English Language Learners (ELLs), free or reduced price lunch, poverty, food stamps, neighborhood income and labor market participation, and school curricular opportunities. This allowed for generalization to the U.S. public school population and for the systematic investigation of school- and classroom-level contextual factors. The NSLM's complete sampling of students within schools also allowed for a comparison of students from different gender and socioeconomic groups with the same expectations in the same educational contexts. To analyze these data, we used the Bayesian Causal Forest (BCF) algorithm, a best-in-class machine-learning method for discovering complex, replicable interaction effects.

Chapter IV examined the interplay of expectations, gender, and socioeconomic status (SES; operationalized with maternal educational attainment). Adolescents' expectations for success in math were meaningful predictors of their early math progress, even when controlling for other psychological factors, prior achievement in math, and racial and ethnic identities. Boys from low-SES families were the most vulnerable identity group. They were over three times more likely to not make adequate progress in math from 9th to 10th grade relative to girls from high-SES families. Boys from low-SES families also benefited the most from their expectations for success in math. Overall, these results were consistent with Mindset × Context Theory's predictions.

Chapters V and VI examined the moderating role of school-level and classroom-level factors in the patterns reported in Chapter IV. Expectations were least predictive of math progress in the highest-achieving schools and schools with the most academically oriented peer norms, that is, schools with the most formal and informal resources. School resources appeared to compensate for lower levels of expectations. Conversely, expectations most strongly predicted math progress in the low/medium-achieving schools with less academically oriented peers, especially for boys from low-SES families.

This chapter aligns with aspects of Mindset × Context Theory. A context that was not already optimally supporting student success was where outcomes for vulnerable students depended the most on student expectations.

Finally, perceptions of classroom stereotyping mattered. Perceptions of gender stereotyping predicted less progress in math, but expectations for success in math more strongly predicted progress in classrooms with high perceived stereotyping. Gender stereotyping interactions emerged for all sociodemographic groups except for boys from high-SES families.

The findings across these three analytical chapters demonstrate the value of integrating psychological and sociological perspectives to capture multiple levels of schooling. It also drew on the contextual variability afforded by representative sampling and explored the interplay of lab-tested psychological processes (expectations) with field-developed levers of policy intervention (school contexts). This monograph also leverages developmental and ecological insights to identify which groups of students might profit from different efforts to improve educational equity, such as interventions to increase expectations for success in math, or school programs that improve the school or classroom cultures.

I. High School Math Progress as a Window into Developmental Dynamics and Societal Inequality

Every year, U.S. adolescents enter high school with dreams of promising academic journeys that will carry them into healthy and productive adulthoods only to then struggle at turning those dreams into reality. Too often, the reasons can be found in the policies, practices, and processes of their schools and classrooms. This disconnect between what young people want and indeed expect to do in school and what they end up doing maps onto society's broader socioeconomic, racial and ethnic, and gender stratification. Thus, it is often taken as evidence that the educational system reinforces this systemic inequality that it was meant to eradicate (Carter, 2018; Downey & Condron, 2016; Duncan & Murnane, 2011; Lucas, 2001; Reardon, 2011).

Just as many adolescents gradually lose their way in high school in the face of systematic barriers and biases, other adolescents—even those facing similar disadvantages—capitalize on the synergy between their own personal capacities and the resources their schools offer them to stay on track toward a more stable and secure future. Understanding how and why academic dreams are dashed or sustained in high school, therefore, requires attention to inequality on the macrolevel, resilience on the microlevel, and institutional dynamics on the mesolevel of more proximate social settings such as schools and classrooms (Bronfenbrenner, 1981). That understanding, in turn, can facilitate the development of strategies to meet the needs of individual students during a historical period of rapid technological transformation (Alexander et al., 2014).

At the heart of this research are key identity groups of students who, through a variety of mechanisms, are at risk of being left behind and/or having their dreams dashed in the U.S. educational system, either generally or in specific but important academic domains. One such group includes young people from socioeconomically disadvantaged families. The socioeconomic segregation of schools and of students within schools leads to the concentration of students with lower-income, less-educated parents within academic spaces with fewer learning opportunities (Mijs & Roe, 2021; Sharkey, 2013). Another group of students to consider is students from historically underrepresented racial and ethnic groups (URG), including Black, Hispanic/Latinx, and Native American students. Because of the overlap of racial and ethnic and socioeconomic stratification in the United States, young people of color in the United States are more likely to come from socioeconomically disadvantaged circumstances. Yet, because processes of racial and ethnic stratification (e.g., interpersonal discrimination, institutional racism) persist above and beyond socioeconomic stratification, students of color also are less likely to have or be able to capitalize on opportunities for enrollment in advantaged schools and classrooms, even when they are not from socioeconomically disadvantaged circumstances (Kohli et al., 2017; Lewis & Diamond, 2015). Gender is another dimension to consider in inequality. Until very recently in the history of the developed world, women were excluded from advanced educational opportunities, leading to long-standing gender disparities (Buchmann et al., 2008; Penner, 2015). More recently, gender inequities have flipped in some circumstances. Boys over the last few decades have disproportionately fallen off the path to *any* advanced education or even high school graduation, opening a large gender gap in many academic indicators (Buchman et al., 2008; Conger & Long, 2010; Reardon et al., 2019). As a result, boys were almost 20 percentage points less likely than girls to be enrolled in higher education in 2020–2021 (Belkin, 2021). Nevertheless, girls remain vulnerable to identity threats within the specific fields of sciences, technology, engineering, and mathematics (STEM). Many high-achieving, confident girls disproportionately move off the path to advanced STEM education relative to boys, especially in the late secondary and postsecondary years. This shift happens even among girls who previously expressed an interest in those fields and could succeed in them (Riegle-Crumb & Morton, 2017; Riegle-Crumb & Peng, 2021). Such gendered patterns are, in turn, complicated by the ways that gender intersects with socioeconomic circumstances and racial and ethnic identities.

Overall, there are several “leaky” pipelines that diminish the pool of individuals who are prepared to advance the frontiers of science and find a meaningful role in the global economy: students from low-socioeconomic status (SES) families, students from URGs, boys leaving both the path to higher education in general and STEM education in particular, and girls disproportionately leaving the latter. This diminishment in the pipeline of scientific talent results in fewer breakthrough solutions to societal challenges and more Americans struggling to earn a living wage (Mouw & Kalleberg, 2010). Understanding the origins of these disparities in high school, therefore, is urgent, as is identifying policy levers that could ameliorate them.

In this spirit, this monograph reports the results of a transdisciplinary and collaborative effort to understand adolescents' expectations for success in school, particularly their expectations for success in the high school math curriculum, due to its essential place in the path to advanced, technical fields. Expectations for success in math are a particular example of a student *mindset*—defined as socialized beliefs that shape self-regulation—which has long held a central role in theories of educational progress in multiple disciplines (Eccles & Wigfield, 2002; Schneider & Stevenson, 1999; Stinebrickner & Stinebrickner, 2014). We build on and inform that tradition by studying the link between adolescents' expectations for success in math and their subsequent math progress—a link representing the translation of *mindset* into achievement—across vulnerable identity groups of students. In doing so, we consider this translation within the *contexts* of schools and classrooms that may disrupt or facilitate the link between expectations for success in math and math progress among students in general and especially those from vulnerable *intersectional identity groups*.

Introducing the Theoretical Perspective Motivating This Research

This research was organized by a general theoretical perspective that we adapted into a specific operationalization. The general perspective, *Mindset × Context Theory* (Hecht et al., 2021; Rege et al., 2020; also see Yeager & Dweck, 2020), orients research on educational equity to the reciprocal influences between young people's psychological orientations and their opportunities to enact those orientations, which are organized and controlled by larger social and institutional settings, such as districts, schools, and classrooms. As such, it connects developmental psychology and sociology in the spirit of human ecology (Bronfenbrenner, 1981).

The main principle of Mindset × Context Theory is that educational equity is predicated on planting the seed (i.e., a personal motivation to achieve) *and* enriching the soil in which the seed grows (i.e., a contextual resource that allows motivation to foster achievement) in a plot of ground that is not already planted (i.e., a context that does not already show near-optimal outcomes) (see Walton & Yeager, 2020). This interplay of seed (mindset) and soil (context) contends that schools and classrooms that have room to grow must create opportunities for young people to achieve, but that those opportunities are effective only if young people are well-positioned to take advantage of them. Otherwise, even young people who want to achieve (and believe they can) may be thwarted when they do not have concrete opportunities to do so. Notably, another principle of the perspective is that the potential benefits of this positive interplay of mindset and context are heightened in the face of societal stratification. Thus, adolescents in vulnerable positions within major stratification systems (e.g., gender, SES, race, and ethnicity) will gain more from this interplay, improving their relative standings with peers in advantaged positions to reduce stratification overall (Dweck & Yeager, 2019; Walton & Yeager, 2020; Yeager & Dweck, 2020). These tenets of the Mindset × Context Theory perspective were borne out by initial results from the National Study of Learning Mindsets (NSLM, see Yeager et al., 2019, 2022). These results showed that a growth mindset promoted key indicators of achievement in schools and classrooms with a growth mindset culture, especially among groups of students who were at risk for low achievement in the first place (also see the College Transition Collaborative; Walton et al., 2023).

Our goal in this monograph was to translate the general Mindset × Context Theory perspective into a more general developmental model that helped us understand the role that expectations for success play in contributing to equity in educational progress within a school system that is highly stratified by family socioeconomic status. To do so, we had to narrow the focus in terms of specific sector of the educational system and in terms of a specific period of the educational career. First, the *math curriculum* is stratified by gender, SES, and race and ethnicity; it is highly cumulative; and it powerfully predicts educational and occupational attainment in the globalized economy (National Science Foundation, 2020). Second, the *first year of high school* is a period when young people face new challenges, when they are at risk of getting lost in the shuffle of larger and more impersonal schools, and when their initial experiences have outsized influence on their future trajectories (Benner & Graham, 2009; Crosnoe & Muller, 2014; Domina et al., 2017; Eccles, 2005). Thus, this sector at this point heightens the potential for disparities related to membership in vulnerable groups and the potential for student expectations, contextual resources, and the interplay between them to matter.

To next step was to narrow the consideration of context. Guided by the developmental literature linking students' learning orientations and behaviors to the interpersonal influences of valued others (Eccles, 2009; Wentzel, 1999), we focused on the normative climates of achievement and learning in schools and classrooms. By normative climates, we mean the standards for success and failure that are put forward (or seemingly put forward) by key actors in schools and classrooms: fellow students and teachers (Allen et al., 2013; Crosnoe et al., 2008; Morgan, 2005; Walton & Yeager, 2020). Specifically, we considered the *school-level peer norms* and the *classroom-level perceptions of stereotyping* (Crosnoe et al., 2008; Yeager et al., 2019).

Conceptualizing and Operationalizing This Research

Figure 1 presents the conceptual model of this study, in which the mindset (expectations for success in math) is translated into a concrete dimension of progress (10th-grade math course-taking progress) at the start of high school differentially across intersectional identity groups. There are several levels to the model. The first level is shown in the individual-level process box. It shows that mindsets shape motivation, engagement, and challenge seeking, and thereby influence persistence in rigorous math courses. However, intersectional identities can influence this process, such that it is weaker or stronger for different groups. Thus, different groups can experience stronger or weaker translation of expectations for success in math into outcomes (e.g., dashed dreams) depending on their vulnerability within the U.S. educational system (Research Question 1). These individual-level processes play out over developmental time, and can be especially important at critical junctures, or turning points, in the educational system (e.g., progress from 9th to 10th-grade math). Next, the individual life course trajectories are nested within ecological (i.e., contextual) forces. These include

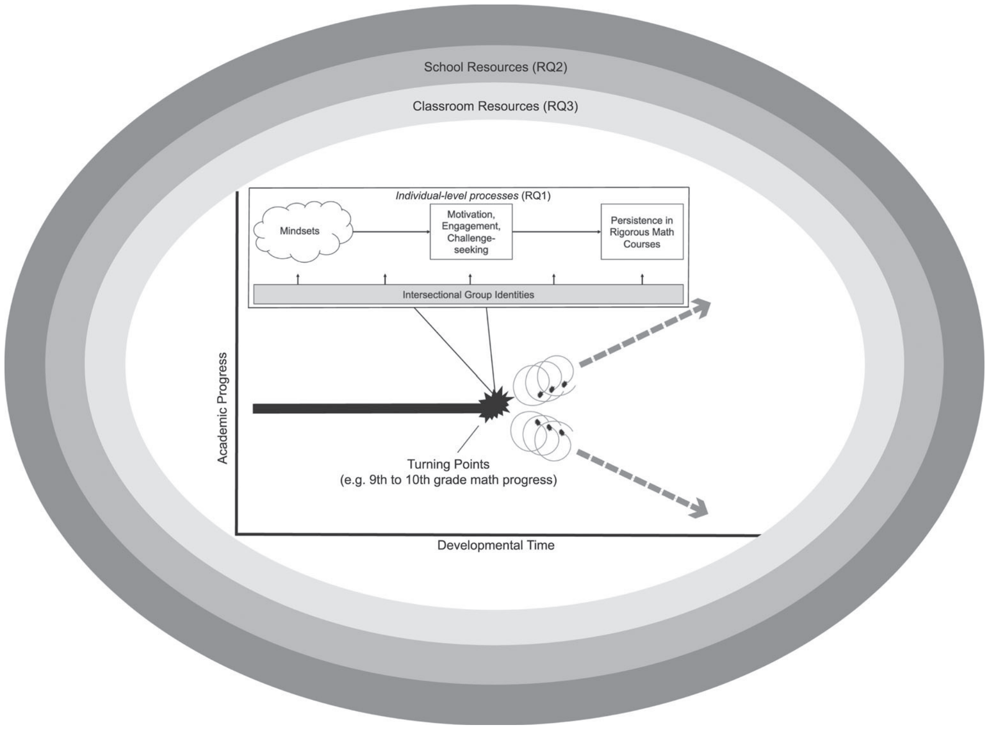

FIGURE 1.—Mindset × Context Theory, an ecological and psychological model, as applied to early high school math progress. The outer-most layer (exo-, macro-, and chronosystems) depicted for completeness, but not studied in the present monograph. Classroom resources = perceptions of classroom gender stereotyping; Mindsets = expectations for success in math; RQ = Research Question; School resources = peer challenge-seeking norms and school achievement level.

schools' peer cultures (e.g., achievement level and academic norms of fellow students at school; Research Question 2) and classroom cultures (e.g., students' perceptions of gendered stereotypes about math; Research Question 3). Although not studied here, we acknowledge that higher-level forces come into play (e.g., the exo-, macro-, and chronosystem). In summary, broader contextual forces moderate the links between students' expectations for success in math and their math progress at the start of high school, particularly among the intersectional identity groups that were most vulnerable to poorer outcomes.

Following this specific conceptual model distilled from general Mindset × Context perspective (Figure 1), this monograph is organized around the following three questions:

1. Which gender and socioeconomic *intersectional identity groups* showed the weakest or strongest links between expectations for success in math and progress through the math curriculum?

2. How did the *school's peer norms* shape the links between student expectations for success in math and math progress across gender and socioeconomic identity groups?
3. How did *perceptions of classroom stereotyping* shape the links between student expectations for success in math and math progress across gender and socioeconomic identity groups?

To operationalize this conceptual model, we drew on data from the NSLM, which was ideally suited to this purpose. As the most recent national, longitudinal study of U.S. public high schools, the NSLM's representative sample allowed us to generalize to the public school population and to conduct a systematic investigation of school- and classroom-level moderation with rich measures of peer norms and perceived classroom stereotyping. The NSLM's complete sampling of students within schools allowed comparison of students from different gender or SES groups (as well as racial and ethnic groups) with the same expectations in the same classroom. Its mixture of survey and administrative data enabled the triangulation of the psychological, interpersonal, and institutional processes at the heart of schooling (Yeager et al., 2019). Finally, its large sample size permitted the use of state-of-the-art, Bayesian, machine-learning methods for answering all questions here. This method can result in more robust, replicable, and trustworthy results than would be possible with conventional regression analyses (Dorie et al., 2019; Hill et al., 2020).

In the next section, we elaborate on the motivation for these hypotheses, the distillation of a conceptual model from the Mindset × Context perspective, and its operationalization with the NSLM. Before doing so, our primary focus on the intersectional identity groups defined by gender and SES needs to be addressed. As described below, theoretical and methodological concerns led to this focus on SES and gender, but, mindful of the ways that racial and ethnic identities intersect with other systems of stratification, we conducted extensive analyses of the role of race and ethnicity as well.

A Deeper Dive into the Conceptual Motivation and Methodological Execution of This Study

The broad context of this study is the historical evolution of the U.S. economy in recent decades that raised the value of higher education (especially in STEM) and, in the process, reinforced the significance of societal-level stratification as both an influence on pathways through the educational system and as a consequence of those pathways. Motivated by this complex phenomenon, our team used the Mindset × Context perspective to conceptualize a study focused on student expectations for success in math and innovatively leveraged the NSLM to operationalize it. We detail each point in the development of this monograph below.

The Broader Context of Educational and Labor Market Inequality

Historical Context

Over the last several decades, the restructuring and globalization of the U.S. economy has transformed the labor market in ways that then transformed the educational system. The gradual shift from an industrial economy to an information economy reshaped the labor market from a pyramid into an hourglass. The pyramid market was characterized by a smaller stratum of higher-paying and more stable professional jobs at the top that required advanced educational credentials, a larger middle stratum of jobs that enabled economic security and promoted social mobility upon the completion of secondary education, and an even larger stratum of lower-paying and more insecure jobs at the bottom of the pyramid that required far less education. In the hourglass market, the middle stratum has been hollowed out, creating a starker discrepancy between opportunities at the top and bottom of the labor market (Autor, 2014; Fischer & Hout, 2006; Mouw & Kalleberg, 2010). This restructuring has increased the value of higher education, especially in specific fields. In the hourglass, college or postgraduate degrees have become the key method of pushing through the bottleneck, particularly if those credentials are in fields that tend to have the highest demand and growth, such as STEM. As a result, the lifelong social and economic returns to higher education—especially in STEM—for both societies and individuals have reached historic levels (Autor, 2014; Black et al., 2021; Hout, 2012).

If higher education has taken on an outsized role in social and economic attainment in this new economy, and STEM education is the most acute example of that outsized role, then understanding what helps or hurts young people in higher education in general and within STEM is significant. Because the math curriculum at the start of high school is so foundational to pathways into, through, and out of higher education, it deserves special attention. Progress in math in high school is highly predictive of college matriculation and graduation, particularly in STEM (Adelman, 2006; Douglas & Attewell, 2017; Jiang et al., 2020). Math also is the most cumulative subject in the high school curriculum. Each math class builds so strongly on what comes before (e.g., Algebra II builds on Algebra I and Geometry) that young people who start off behind or fall behind early on have great difficulty catching up with their peers. In part, the cumulative nature of high school math reflects the incremental nature of math skill-building and the prerequisite structure of math course enrollment, but it also reflects the ways that past coursework signals to others—correctly or incorrectly—young people's preparation and suitability for future opportunities (Crosnoe & Huston, 2007; Domina & Saldana, 2012; Tyson & Roksa, 2016). Within this cumulative high school curriculum, the starting point becomes quite important. In theory, students' math course enrollment in the first year of high school is predicated on their middle school performance and future goals. In reality, it may also be influenced by teachers' biased perceptions (good or bad) about adolescents' ability and preparation and parents' understanding of the nature of the new curriculum and what the long-term consequences of initial curricular positions are. In particular, whether adolescents begin high school in Algebra 1 or Geometry—and how they perform in either—determines their future opportunities for advanced math and science coursework through high school (Crosnoe, 2009; Crosnoe & Huston, 2007; Langenkamp, 2010; Schiller, 1999).

Data Showing the Importance of Early Math Progress

To further illustrate why math progress early in high school represents a critical point for long-run adolescent development, Figure 2 previews the complete set of high school math course-taking patterns in the present monograph's dataset (NSLM) among students who attended the same high school from 9th through 12th grades ($N = 9{,}431$). Thicker pathways indicate more common math transitions for students. The most common course-taking pattern was for students to start Algebra 1 in 9th grade and advance to Geometry in 10th grade, Algebra 2 in 11th grade, and precalculus or advanced math in 12th grade. Despite starting at a lower level, these students could still complete a rigorous math curriculum by the end of high school. Some of these Algebra 1 students were diverted in 10th grade, as shown by the pathway highlighted in blue. The overwhelming majority of these diverted Algebra 1 students did not reach a math level above Algebra 2 by the

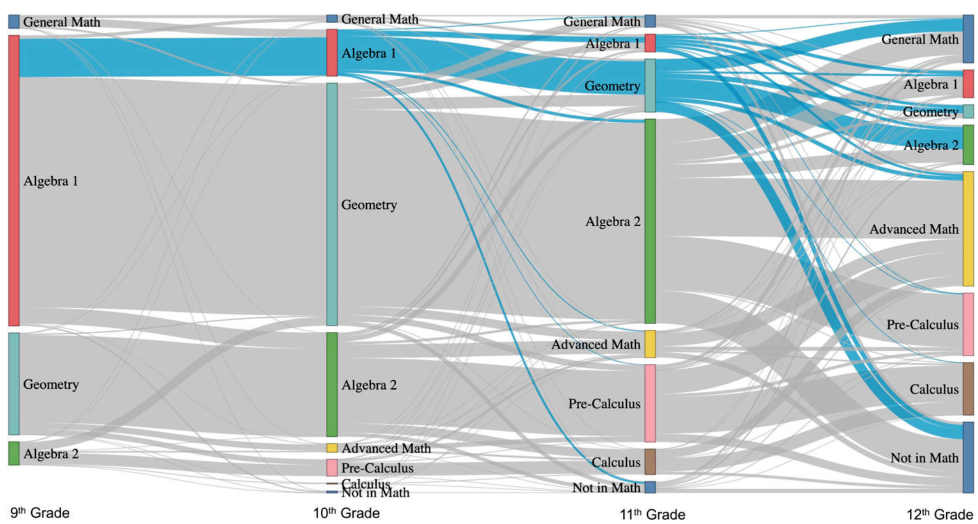

FIGURE 2.—Adolescents' math course-taking pathways through high school. The sample includes 9,431 students with 9th- through 12th-grade course-taking records from their original sample school. It excludes students who took advanced math in 9th grade and other students that took uncommon pathways. Excludes students who left their original sample high school before 12th grade.

end of high school. In fact, many did not continue advancing math levels after completing Geometry in 10th grade.

Figure 2, therefore, illustrates why this ecologically informed study focuses on the transition from 9th- to 10th-grade math. This transition is when students are most likely to repeat a course. Also, unlike later high school transitions, the 9th- to 10th-grade transition is less complicated by student choice. Specifically, once students reach Geometry or Algebra 2, they have more choice about whether they would like to take more advanced math, less advanced math, or stop taking math altogether. Thus, students who do not progress from 9th to 10th grade not only lack the opportunity to reach rigorous math levels in high school, but they also have less choice in their math course-taking than do students who complete Geometry earlier in their high school career.

Another reason to focus on this transition is that it sets the stage for what adolescents can accomplish in high school and beyond. Prior research has shown that completing advanced math in high school is important for college entry, college completion, earnings, and even health later in life (Adelman, 2006; Carroll et al., 2017; Rose & Betts, 2004). A preview of our data (Figure 3) showed that disparities in adolescents' graduation status, rigorous high school course-taking, and postsecondary enrollment vary by whether they progressed in math from 9th to 10th grades. Figure 3 displays the proportion of adolescents who achieved each of these academic milestones among those who advanced in math between 9th and 10th grade (their math

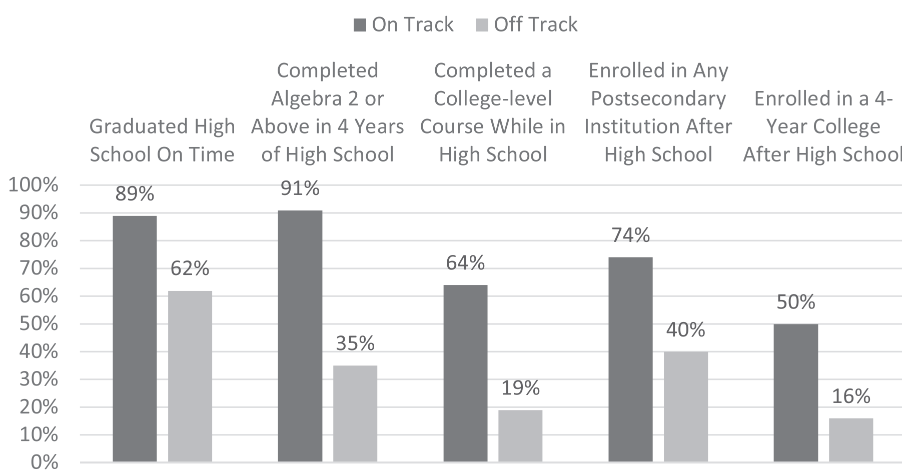

FIGURE 3.—High school and postsecondary outcomes, by On Track versus Off Track math course progress from 9th to 10th grade. On Track students advanced at least one course level between 9th and 10th grade. Off Track students repeated the same course level or decreased course levels between 9th and 10th grades. Graduation status comes from school records ($N = 10{,}446$). Math and college-level course-taking (including AP, IB, and Dual Credit) are for students with 4 years of course-taking data from schools ($N = 7{,}529$). Postsecondary enrollment was determined from National Student Clearinghouse among students in schools that gave us student identifying information ($N = 10{,}414$).

progress was “On Track”) and those who did not (their math progress was “Off Track”).

The disparity in long-run outcomes between adolescents who did and did not progress in math between 9th and 10th grades was 27% for high school graduation, 56% for advanced math course-taking, 45% for college-level course-taking, 34% for postsecondary enrollment, and 34% for 4-year college enrollment. Of course, these gaps were partly related to adolescents' prior skills, background, and school context, but they highlight the importance of early high school math progression for success in high school and beyond. Figures 2 and 3, therefore, illustrate why zeroing in on a particular moment in the lifespan—math progress in the transition to high school—can act as a window into the processes that create or sustain inequalities.

Summary: Rationale for the Present Study's Focus

Thus, social mobility in the modern economy is strongly influenced by the attainment of higher education (especially in STEM), which is strongly influenced by high school math progress, which is strongly influenced by initial high school math placement and achievement. If adolescents from different intersectional identity groups start high school math on equal footing, with similar expectations for success in math and similar opportunities to translate those expectations into math progress, then the critical nature of high school math and its life course antecedents may forecast reduced social and economic disparities across groups in the future. Yet, we know that many intersectional identity groups do not have that equal footing. After all, high school math progress—including initial enrollment and achievement—is systematically differentiated by factors such as gender and SES (Frank et al., 2008; Penner & Paret, 2008). This differentiation reflects the role of family background in securing resources and supports for academic enrichment that are especially important to math learning (e.g., tutoring) prior to high school. It also reflects the tendency for group identities to elicit stereotyping about math ability that may lead to differential treatment by adults and self-doubt among adolescents themselves (e.g., the chilly math classroom or math anxiety) in ways that differentially steer student groups toward or away from advanced math at the start of high school (Foley et al., 2017; Paschall et al., 2018; Riegle-Crumb & Humphries, 2012). Again, race and ethnicity also can stratify high school math, in part through persistent socioeconomic disadvantages within communities of color but also though nonsocioeconomic mechanisms (e.g., anti-Black racism, implicit biases), and it can moderate gender differences in math (e.g., Fahle et al., 2020; Hanselman & Fiel, 2017; Riegle-Crumb & Grodsky, 2010). Thus, understanding intersectional gender and socioeconomic disparities in high school math progress needs to also pay attention to interdependent racial and ethnic disparities.

These highly stratified patterns of high school math progress—including at the start of high school—then foreshadow the stratification of higher education and the labor market. For example, both boys and girls from socioeconomically disadvantaged families are far less likely to matriculate in or graduate from college than their peers from more privileged backgrounds, and they are underrepresented in STEM majors in college and STEM sectors of the labor market (Chetty et al., 2014; Institute of Education Sciences, 2020). Girls have higher levels of educational attainment than boys almost across the board in the United States, but STEM fields are the most glaring exception to that rule. Consequently, women are also significantly underrepresented in STEM occupations (Black et al., 2021; Budig et al., 2021; DiPrete & Buchmann, 2013; Kalev, 2014).

Any psychological, social, and other challenges that interfere with math progress at the start of high school, therefore, have cascading consequences for the future, both for individual youth but also a society that is increasingly dependent on robust STEM activity. Understanding those challenges in ways that inform policy action has been a major source of interdisciplinary social and behavioral science. Various theoretical perspectives point to different ways to approach this issue, and the results of those different approaches contribute to the growing base of knowledge that is so important to solving this societal problem and helping individual youth.

The Conceptual Model

As already introduced, the theoretical perspective we draw on here—the Mindset × Context perspective—points us to considering the agency of individual youth from differently vulnerable intersectional identity groups amidst a set of constraints and opportunities created by the settings in which they live. We can break down each part of this perspective and how it sets up a concrete piece of the conceptual model for this study.

Mindset

First, the mindset component of the perspective emphasizes the critical role of young people's psychological resources for charting their own course through the educational system. Here, we conceptualize mindset in terms of expectations for success in math and conceptualize the translation of mindset into achievement in terms of the association between such expectations and progress in math during the first year of high school. A long history of research in psychology finds that individuals' expectations for success, also known as self-efficacy beliefs or self-concepts, affect their motivation, engagement, choice of learning activities, and performance (e.g., Bandura, 1982; Eccles & Wigfield, 2020; Harter & Pike, 1984; Marsh, 1990; Schunk & DiBenedetto, 2021), and this research is echoed by similar literatures in sociology (Bozick et al., 2010) and economics (Stinebrickner & Stinebrickner, 2014). Adolescents who believe they can be successful on a given task or within a given area are more likely to set goals, select more challenging activities, and engage in more effective learning strategies.

Adolescents' expectations at the start of high school are a culmination of their prior academic experiences, including their academic performance and signals they receive from their teachers and peers about their abilities, as well as broader societal stereotypes about whether a person like them can be successful (Eccles & Wigfield, 2020).

Context

Second, the context component of the perspective emphasizes how institutional settings characterized by practical, academic, and socioemotional resources offer supportive opportunities or, alternatively, constraints that block the translation of student mindsets into concrete markers of academic progress (e.g., grades, course enrollments, and test scores). Here, we conceptualize context in terms of the informal processes of schools and classrooms as defined by school peer norms and classroom perceptions of stereotyping. As opposed to formal processes of school, which refer to the inputs and outputs of the educational system most concretely linked to its manifest function of creating a skilled workforce and an informed populace (e.g., staffing, curriculum, funding), informal processes refer to the social and psychological undercurrents of schooling. They provide the mechanisms through which schools and classrooms offer safe, healthy, and equitable spaces for young people to come of age. In particular, they are manifested in the norms and values that emerge when students and staff interact over time and then enable young people to feel secure, supported, and encouraged when pursuing learning and achievement (e.g., proacademic climate, an ethos of caring, progressive ideas about equity) (Allen et al., 2013; Bryk & Schneider, 2003; Coleman, 1961). Academic contexts with positive informal processes can help young people with strong psychological orientations to schooling (e.g., high expectations for success in math) reach their potential and/or foster higher-than-expected success among others without these orientations. Academic contexts with negative informal processes are more toxic settings that blunt young people's progress no matter their psychological orientation, undermining academic prospects across the board but also blocking some young people from capitalizing on their own internal strengths and capacities (Crosnoe, 2011). Importantly, informal processes can differ from school to school, and individual schools can also be internally heterogenous in their informal processes.

On the school level of context, our interest is in the informal processes that emerge among peers in the student body; in particular, proacademic norms that counter the traditional narrative about the negative influences of adolescent peers. Indeed, peers can model achievement- and learning-oriented behavior and attitudes (e.g., showing that doing well in school enhances status), create opportunities to invest in academic pursuits (e.g., demanding more advanced classes or organizing social life around studying or school activities), and share academically relevant information (e.g., signaling which courses to take or offering guidance on homework). The prevailing academic patterns of the student body, therefore, represent a key dimension of informal processes that positively socialize young people beyond—or even despite—the school's formal processes related to structure, policy, and composition. Such school-level peer norms may include how much effort students put into their schoolwork and how important academic achievement is to their lives. On the classroom level of context, our interest is in the informal processes that emerge within classrooms under the guidance of teachers; in particular, messages that teachers convey about who is and who is not expected to do well (i.e., are certain kinds of students "math people"?). Indeed, when adolescents perceive that their teachers demonstrate through attitudes or pedagogical practices a belief that students can develop cognitive and academic skills regardless of who they are, where they came from, or their prior level of achievement, they are more likely to internalize that they have what it takes to make significant progress and that they should pursue such progress. Such classroom-level perceptions of teachers' beliefs may include whether they praise certain students for getting answers quickly and expect less from other students who are not "math people." Notably, informal processes on the school and classroom levels might interact with mindsets at the individual level. Supports on one level could counterbalance a lack of supports on the other, supports in both can multiply advantages for students, and deficits in both can create a double disadvantage.

Stratification and Inequality

Third, Mindset × Context dynamics are inextricably tied to broader patterns of stratification in our society, with the perspective arguing that these dynamics are more impactful (in positive and negative ways) for identity groups vulnerable to poorer performance at the intersection of multiple systems. Here, we conceptualize intersectional identity groups in relation to gender (adolescents who identify as girls relative to those who identify as boys) and SES (adolescents with college-educated parents relative to those whose parents did not go to college) while paying additional attention to how they connect to racial and ethnic identities. Math is a gender-typed activity, with enduring cultural messages that boys are more adept at math and prepared for STEM than girls (Leslie et al., 2015; Meyer et al., 2015). These messages can dissuade girls from math, engender self-doubt about math ability, and lead to implicit biases and outright discrimination even though gender gaps in math performance and STEM attainment have narrowed in recent years (Eccles, 2005; Riegle-Crumb & Humphries, 2012). At the same time, school, in general, has increasingly been stereotyped as a female gender-typed activity, as masculinity norms often dictate that boys—especially in high school—should not be enthusiastic about learning in school (Hartley & Sutton, 2013; Heyder & Kessels, 2013, 2017). Turning to SES, the role of parent education in academic progress is, in part, channeled through other socioeconomic advantages that educational attainment facilitates. For example, stable and well-remunerated employment allows parents to accrue financial resources that they can deploy to support their children's academic trajectories. Yet, this role goes beyond financial resources. College-educated parents tend to have more inside knowledge about how the educational system works, higher status and more power that they can capitalize on in dealing with schools, and more access to social networks that can advance their children's interests (Attewell et al., 2007; Destin et al., 2019; Lareau, 2011; Weininger et al., 2015), especially in contexts of uncertainty such as the highly complex and opaque math curriculum (Crosnoe & Muller, 2014). Intersectionally within the domain of math, the most vulnerable identity groups would be boys from lower-income families, increasing their potential reactivity to Mindset × Context dynamics.

Hypotheses

Specifying the general Mindset × Context perspective in these ways, the conceptual model of this study (see Figure 1) presents three broad sets of hypotheses:

1. Adolescents' expectations for success in math at the start of high school will be more strongly associated with progress in math in 10th grade for the intersectional identity group most at risk of not progressing in math: boys from low-SES families.
2. This link between expectations for success in math and math progress will be stronger in schools that are not already optimally achieving and that have academically oriented peer norms.
3. This link between expectations for success in math and math progress will be stronger in classrooms with high perceived gender stereotyping because stereotyping will be especially harmful to students with low expectations.

As described in Chapter III, each of these broad sets of hypotheses can be broken down and/or elaborated on into more detailed hypotheses that will then be tested in subsequent chapters. Recognizing how persistent racial and ethnic disparities in the United States can overlap with and/or exacerbate other kinds of disparities in young people's orientations to school, progress through school, and school location (Beasley & Fischer, 2012; Irizarry, 2021; Riegle-Crumb, 2006; Steele, 1997), we should reiterate that we supplemented this conceptual model focused on the intersection of gender and SES by also examining racial and ethnic patterns. Interpreting the higher-order interactions among expectations, school context, gender, and SES was challenging enough, so we limited discussion of the further moderation of these interactions by racial and ethnic identity (which showed magnified disparities for students from URG) to Chapter IV. Young people of color in the United States are more likely to come from socioeconomically disadvantaged circumstances. Yet, because processes of racial and ethnic stratification (e.g., interpersonal discrimination, institutional racism) persist above and beyond socioeconomic stratification, students of color also are less likely to have or be able to capitalize on opportunities for enrollment in advantaged schools and classrooms, even when they are not from socioeconomically disadvantaged circumstances (Kohli et al., 2017; Lewis & Diamond, 2015).

The Methodological Plan

Testing the hypotheses derived from the specific conceptual model that we distilled from the general Mindset × Context perspective involves extensive operationalization and analyses of the NSLM. Chapter III describes the NSLM, its measures, and our statistical plan for analyzing this dataset in detail, but we highlight the main points here.

Dataset

The NSLM was a randomized trial and longitudinal study conducted with a nationally representative sample of over 16,000 9th-grade students in 76 public schools in the United States during the 2015–2016 school year (see Yeager et al., 2019). It used an experimental design with random assignment; results of the experimental manipulation have been reported previously (Yeager et al., 2019, 2022) and are not the focus of this monograph. The treatment group received a short (<50-min), online, classroom-based, two-session growth mindset intervention in which they learned about how the brain learns and develops and what that means for schooling. The control group received a general lesson about adolescent brain development that was not explicitly tied to the idea of growth and malleability. Prior work has documented the positive causal effects of the mindset intervention on various academic indicators as well as the variability of these effects by school and classroom (Yeager et al., 2019, 2022). Consequently, this monograph did not delve into those experimental effects. Crucially, the study also surveyed students and their math teachers before the intervention was administered. At the end of the school year, we collected and coded their official transcripts. These survey measures and administrative outcomes are analyzed here.

Operationalizing Key Constructs

The NSLM data allowed the operationalization of adolescents' expectations for success in math (see Hulleman & Harackiewicz, 2009) and math progress, measured as the change in the level of the math course in which adolescents enrolled in 9th and 10th grades (following coding conventions from multiple national studies based on population patterns of U.S. students' progression through the math curriculum; see Riegle-Crumb, 2006). The association between these two constructs—representing the translation of expectations for success in math into math progress—was the focus of this monograph. The operationalization of contextual resources included school-level measures of peers' orientation towards achievement (achievement-level and norms of academic challenge-seeking), and a classroom-level measure of perceptions of gender stereotyping in math by teachers and peers in the classroom. This contextual examination of the NSLM nested young people within their 9th-grade math classrooms, which are in turn nested within their high schools. Intersectional identity groups were operationalized in terms of the intersection of SES, indexed by parent education (whether an adolescent had a college-educated mother or not) and gender; these identity groups were analyzed as moderators of students' expectations for success in math.

Analytic Approach

These analyses employed a modeling strategy that estimated differences between students within the same context, with random slopes for each school (or classroom) to understand the school- or classroom-level moderators of interest. A validated but relatively recently developed Bayesian machine-learning statistical method examined complex, multilevel moderation effects (the BCF algorithm; Hahn et al., 2018; Yeager et al., 2022). This technique allowed us to better-approach causal inferences about the effects of expectations for success in math (Dorie et al., 2019), and allowed us to investigate how adolescents' expectations, school factors, and classroom factors predict math outcomes in different ways for students from different intersectional identity groups.

Significance of This Research

This monograph presents the results of our analyses of a conceptual model growing out of Mindset × Context Theory. The next two chapters ground this conceptual model in a history of mostly lab-based research in psychology and large-scale research in sociology (Chapter II) and provide an overview of the NSLM dataset and our analyses of it (Chapter III). Chapter IV explores gender and socioeconomic differences in the association between adolescents' expectations for success in math and math progress at the start of high school, with an additional analysis of the role of race and ethnicity. The next two chapters focus on school-level (Chapter V) and classroom-level (Chapter VI) moderation of the gender and socioeconomic differences in expectations for success in math, math progress, and the interplay of the two across intersectional identity groups. Chapter VII concludes with the theoretical and policy implications of these results.

This research contributes to developmental science of education and inequality in several key ways:

- Putting forward a theoretical perspective that can guide research attempting to link psychological processes to larger institutional and structural forces, and sociological theories about these forces.

- Presenting the most recent, generalizable evidence about gendered patterns of socioeconomic inequality in high school math.
- Introducing a public, longitudinal dataset to the field that can be used to examine contextualized developmental processes while increasing the generalizability of findings.
- Guiding policy that aims to promote academic success and reduce academic disparities through adolescent-focused interventions and larger school reforms.

II. Applying Mindset × Context Theory to High School Math

This chapter lays out a framework, Mindset × Context Theory, that can be leveraged to anticipate and interpret how students' psychological resources—their mindsets—have different effects on academic outcomes in different contexts. Mindset × Context Theory emphasizes that policy solutions to the problem of insufficient math progress will require attention to psychological factors (such as expectations for success) as well as contextual factors (such as the support of peers or teachers).

Mindset × Context Theory

The two terms comprising Mindset × Context Theory need to be defined and described in detail. After doing so, we can discuss how these two concepts interact.

Mindsets

Mindsets are situation-general, socialized belief systems that guide interpretations of the social world to influence self-regulation processes during goal pursuit (see Dweck, 2017; Dweck & Yeager, 2019; Hecht et al., 2021). In this study, the mindset of interest was a person's expectations for success, a concept which has a long history in developmental research (Eccles & Wigfield, 2002, 2020; Muenks et al., 2018).

What do these different components of the definition mean? *Situation-general* means that mindsets are not beliefs about a particular event—such as one test or one interaction with a peer or teacher. Instead, they are beliefs about categories of attributes or experiences, such as one's potential for future success in math. *Socialized* means that they are the product of prior experiences with goal pursuit and with socializing environments, such as parents, peers, and teachers (Eccles & Wigfield, 2002; Wentzel & Looney, 2007). They are not solely situationally constructed or ephemeral. We say that mindsets guide interpretations of specific situations in the social world, because they give ambiguous events—such as a moment of frustration or isolation—larger meaning. For example, when people expect to do well, they may appraise an experience of failure as a momentary setback, but, when they expect to do poorly, they may think the failure is a sign that their fears about being incompetent are going to be confirmed. Thus, mindsets offer starting assumptions that are later tested out in daily experiences in pursuing goals (see Walton & Wilson, 2018; Walton & Yeager, 2020). Mindsets affect *self-regulation* styles through this meaning-making process. For instance, people who expect to do well and then make positive appraisals of frustrations go on to use more resilient self-regulation techniques, such as trying the problem a different way, increasing effort, or asking for help appropriately. When people expect to do poorly, however, they tend to use less resilient self-regulation techniques, such as procrastination, self-handicapping, withdrawing effort, or otherwise hiding their deficiencies to avoid confirming their own or others' low opinions of their abilities.

Research has identified many different mindsets in the literature, and all have some relation to expectations for success in math, the mindset of interest in this study. Examples include growth (versus fixed) mindsets (also called implicit theories; see Dweck, 2006; Dweck & Yeager, 2019; Yeager & Dweck, 2012), belonging mindsets (also called belonging uncertainty; Walton & Cohen, 2007, 2011), relevance mindsets (also called utility value; e.g., Harackiewicz et al., 2016; Hulleman & Harackiewicz, 2009), purpose mindsets (e.g., Reeves et al., 2020; Yeager et al., 2014), stress mindsets (Crum et al., 2020; Yeager et al., 2022), and more. Here we focused on expectations because they are thought to be one central process through which the different mindsets relate to achievement outcomes. This fact will allow us to develop a broader theoretical framework that may well generalize across the different specific mindsets in the literature.

Another key reason to focus on expectations is that they have long been a target of policy action. Dating back to Clark and Clark's (1947) seminal research on self-esteem for Black and White students and the ensuing Brown v. Board of Education decision integrating U.S. public schools (Warren & Supreme Court Of The United States, 1953), enormous effort has been put into raising expectations for success among students from historically segregated and marginalized groups. To this day, investments also have been made in narrowing gender inequalities in expectations for success in math and science (Hulleman & Harackiewicz, 2009; Saujani, 2017). Is it enough, though, for adolescents to have high expectations, or do they need support from their school and classroom learning contexts to realize their high expectations? This question highlights the importance of the context part of the model.

Contexts

As previewed in Chapter I, classic sociological theories of inequality (Coleman & Hoffer, 1987; Domina et al., 2017) define context in terms of the resources it provides for individuals who are striving for social or economic success in a given political system. In the educational system, resources can be *formal*, which refers to the written policies that provide access to high-quality teachers, curriculum, and schools (Coleman & Hoffer, 1987; Duncan & Murnane, 2011). Resources can also be *informal*, which refers to emergent factors of the social milieu, such as the peer or classroom culture (Coleman, 1961). In general, both formal and informal resources tend to be less abundant and/or accessible for members of groups that have been historically marginalized in a domain, and more abundant and accessible for members that have been afforded greater power, privilege, and influence in a domain. Thus, resources in the context tend to reproduce inequality. At the same time, the marginal benefit of providing additional resources—either formal or informal—tends to be greater for members of marginalized groups, because any additional resource above the status quo makes a relatively greater difference for those who have less of it. Thus, increasing the availability of a contextual resource that is sorely needed by a given group offers one important way to narrow group disparities.

Mindset × Context Interactions

Although sociological theory speaks to how resources directly affect outcomes across groups, it has not yet systematically explained how resources interact with the psychological orientations—or mindsets—that students bring with them to the school context. Mindset × Context Theory seeks to do just that by combining the psychological perspective on culturally learned mindsets with the sociological perspective on inequality.

According to Mindset × Context Theory, contextual resources could have two kinds of moderating effects (Bailey et al., 2020; Miller et al., 2014). First, the context could have a *compensatory* effect. Imagine that a student's mindset is a kind of internal psychological resource. An external contextual resource, such as a well-run school with dynamic and motivating teachers, could compensate for a student's lack of that internal resource. Empirically, the compensatory effect would mean that a student who is low on a positive mindset factor would not be any worse off than a student who was high on that factor, provided that they were in a context with abundant resources.

Alternatively, the context's resources could have a *complementary* effect. This effect would occur if the student's mindset and the context's resources work together to result in progress through the educational system. In a complementary interaction, a mindset is like a "seed" that must be planted in fertile "soil" to have effects (Walton & Yeager, 2020). This pattern has also been called the *affordances* pattern of results, because the context is affording, or supporting, the student's implementation of their mindsets (Hecht et al., 2021; Walton & Yeager, 2020). This affordances language emphasizes that a mindset is like a starting hypothesis about a context, but students must apply that hypothesis to interpret specific, ambiguous situations. If the context does not afford an opportunity for the student to make the more optimistic appraisal of the situation, then the student may not benefit from the mindset. Likewise, if the context provides resources, but the student is not psychologically prepared to attend to and positively appraise them, then the student may not fully benefit from the context. Empirically, the complementary effect would show up as a positive interaction between a student's positive mindset and the positive contextual supports for that mindset, when predicting academic progress outcomes. This view has also been called an *accumulated advantages* pattern (see Bailey et al., 2020; Miller et al., 2014), because it is the people who already had more of a beneficial mindset already who then go on to profit more from the resources in the context.

There is one final untested corollary of a complementary effect. Consider negative mindsets and negative contextual factors—factors that do not just fail to provide resources, but that actively undermine a group's pursuit of a given goal. In principle, the complementary effect of a negative mindset and a negative context would give rise to an *accumulated disadvantages* effect. Those with a negative mindset, in an achievement-suppressing context—for instance, a context with rather severe stereotyping of one's group—would display the poorest outcomes overall. We extend Mindset × Context Theory to examine the accumulated disadvantages hypothesis in Chapter VI.

The Status of Mindset × Context Theory

Tests of Mindset × Context Theory so far have come from field experiments (Reeves et al., 2020; Walton et al., 2023; Yeager et al., 2019, 2022). These field experiments have manipulated a particular mindset and assessed how the benefits of that mindset have varied across different contexts.

The following studies have mostly shown a compensatory interaction effect for formal resources (i.e., positive mindsets are less necessary in well-resourced contexts that already lift outcomes for most groups) and a complementary interaction effect for informal resources (i.e., positive mindsets depend on informal processes that make the mindset feel "true"). While this research has isolated the causal effects of mindsets—but not of expectations—and how this causal effect differs in various settings, it has not yet examined the role of mindsets in group-based inequality, such as gender or socioeconomic status. Nor has the research fully examined the possible complementary effects.

Evidence From the NSLM

The first two preregistered analyses from the NSLM assessed how the benefits of a short, online, student-directed growth mindset intervention on students' grade point average (GPA) varied across individuals, schools (Yeager et al., 2019), and math teachers (Yeager et al., 2022). These analyses revealed that the growth mindset intervention's effects on student GPA were greater among lower-achieving students (Yeager et al., 2019) and students who previously reported more of a fixed mindset (Yeager et al., 2022). Thus, at the level of individual differences, the intervention changed outcomes the most among students who previously were vulnerable to the processes targeted by the growth mindset (also see Andersen & Nielsen, 2016; Porter et al., 2021).

Further, past NSLM analyses examined the moderating effect of context. At the school level, peer norms were a moderator. Peer norms were measured using a behavioral task (called the “make-a-math-worksheet” task; Rege et al., 2020) that assessed students' desires for academic challenges that could teach them something new, even if they did not get all the answers correct (a “learning” or “mastery” goal) (Elliot & Church, 1997; Elliott & Dweck, 1988). Individual students' choices, from the control group, were averaged at the school level to index peer norms. In contexts with greater challenge-seeking peer norms, the growth mindset intervention had larger and substantively meaningful (in terms of effect size) benefits for GPA. Few effects emerged in contexts with weaker challenge-seeking peer norms. At the classroom level, teachers' mindsets about the malleability of ability were a moderator. In classrooms taught by teachers who reported more of a growth mindset, there were meaningfully large treatment effects on math GPA. There were few effects on math GPA when teachers reported more of a fixed mindset. The overall conclusion from the NSLM, then, was that treatment effects were larger among vulnerable groups who were in school or classroom contexts with more supportive informal resources. This conclusion was bolstered by the NSLM's use of a large, nationally representative sample and conservative, Bayesian machine-learning analysis methods. It was also supported by subsequent randomized experiments that manipulated the classroom culture and directly illustrated their moderating role (Hecht et al., 2023).

Evidence From Experiments to Promote Belonging and Purpose Mindsets

Walton and Yeager (2020) reviewed several other studies showing complementary (affordances) patterns of results, similar to the NSLM. A large multisite experiment (Walton et al., 2023); $N = 26{,}911$ students, $k = 22$ colleges) conducted by the College Transition Collaborative (CTC) evaluated a short online social belonging intervention that had, in previous experiments, improved the college persistence and achievement outcomes for first-generation college students, students of color (Walton & Cohen, 2011; Yeager et al., 2016), and women in male-dominated engineering majors (Walton et al., 2015). The CTC study found that the belonging intervention improved full-time enrollment the year after the study among students whose social class and racial and ethnic identity groups historically showed greater disparities in outcomes and in contexts that afforded more of an opportunity for belonging for members of those groups (Walton et al., 2023).

A field experiment conducted by Reeves and colleagues (2020) manipulated the presence of affordances, or supports, in a classroom culture to test whether they would enhance the academic benefits of a student's mindset.

This study focused on the purpose mindset, which is the belief that schooling is an opportunity to acquire skills that help you to make a contribution to something larger than yourself (Damon et al., 2003; Hill et al., 2010; Yeager & Bundick, 2009). In this experiment, 7th and 8th-grade students completed a short, online purpose mindset intervention or a control intervention. A few weeks later, teachers provided students with hand-written notes encouraging them to view a test preparation assignment as an opportunity to take a step toward their self-transcendent purposes, or with control notes. The study showed strong evidence for a complementary Mindset × Context interaction: the student's mindset and the teacher's note each had an effect only when the other was in place. These results were strongest for the group of students who previously had the lowest scores in the English class—nonnative English speakers. Thus, this experiment also provided evidence for the notion that mindsets have larger effects among vulnerable students in supportive contexts.

Unanswered Questions in Mindset × Context Theory Addressed Here

For Which Gender and Socioeconomic Identity Groups are Mindset Associations Weaker or Stronger?

Mindset × Context Theory is intended to explain a range of group-based inequalities. Research on moderation of psychological intervention effects to date, however, has focused on separate identities, such as gender, SES, race, or ethnicity (e.g., Murphy et al., 2020; Reeves et al., 2020; Stephens et al., 2014; Walton & Cohen, 2007, 2011; Walton et al., 2015; for notable exceptions, see Harackiewicz et al., 2016; Walton et al., 2023). This narrow focus has left many questions about the connections among identities, and their interplay with mindsets, unanswered.

Usually, studying the connections among systems of stratification and identity groups is challenging because of sample size issues that arise from studying rarer subgroups. Consider that studying only two social identities interacting with a single mindset across even just one context factor implies a four-way interaction, which can be difficult to detect reliably in small samples. Studying multiple identities or multiple context factors can make the problem even greater, which is why a large heterogeneous sample is needed to study more complex identities directly. Here we use the large, nationally representative sample from the NSLM to address this gap in the literature. Drawing on the framework of Choo and Ferree (2010), we take a group-focused perspective on the connection among different identities and examine the possibility of "multiple jeopardy" (King, 1988) in the transition to high school. Even with this strength, a limitation of our research was that we did not have statistical power to ask these questions separately for each of the major racial and ethnic groups in the United States.

The two dimensions of inequality we focused on primarily were gender and SES. As explained in Chapter I, these factors stratify access and opportunity to higher-level STEM coursework and workforce opportunities. On average, students from high-SES families are taught in more advantaged contexts that lead to higher academic achievement, challenge-seeking, and progress toward valued credentials. Yet, the story with respect to gender can be more complicated, as noted in Chapter I. Women and girls in the United States and in many other contexts around the world are subjected to negative intellectual stereotypes about their potential in math and science (Spencer et al., 1999; Zhao et al., 2022) and they often face anti-intellectual peer norms that discourage immersion in their studies (Gordon et al., 2013). This bias can keep them out of the upper echelon of STEM performance. Nevertheless, girls are equally represented in advanced math at every grade level in high school and in the first few years of college as compared with boys (Riegle-Crumb & Peng, 2021). Boys—and especially boys from low-SES families—have lower rates of math success and later college matriculation, perhaps in part due to the perceptions that doing well in school and caring about one's education are feminine attributes (e.g., Hartley & Sutton, 2013; Heyder & Kessels, 2013, 2017). In fact, boys' inclusion in higher education has been declining for over 40 years. After the 2020–2021 school year, the year in which the present study's participants should have been in their second year of college, 59.5% of college students were girls, and only 40.5% were boys (Belkin, 2021).

In addition, disparities by race and ethnicity persist in access to educational opportunities in general, and STEM specifically. Students from underrepresented racial and ethnic groups (URGs), including Black, Hispanic/Latinx, and Native American students, on average attend lower-quality schools with fewer resources (Fahle et al., 2020). Even when from high-SES families and when attending higher-quality schools, these students experience inequality in the rigor of their math course offerings (Hanselman & Fiel, 2017; Quillian, 2014). Negative stereotypes about which racial and ethnic groups have innate abilities or can be successful in school and in society are common even among teachers (Chin et al., 2020). This means that groups of Black and Hispanic/Latinx students, on average, do not reach the same level of math achievement as their peers, even when they come from high-SES families or have high achievement levels (Reardon & Robinson, 2008). There is some evidence that these patterns differ by gender; girls from URGs, on average, have higher academic achievement than boys from URG (Riegle-Crumb et al., 2018). While racial and ethnic identities could not be investigated with sufficient power in our contextual moderation analyses, we attended to these disparities in Chapter IV.

Overall, this previous evidence raised intriguing questions about how SES and gender jointly interact with expectations for success in math to create inequitable academic progress in math. Should girls—the traditionally stereotyped group—show the greatest benefit of high expectations for success in math? Or should boys—the group with lower achievement—benefit the most from high expectations? We can also ask how gender differences vary by SES. Should these patterns be greater for youth from high-SES families, perhaps because their families have more resources to support their expectations for success in math? Should they be greater among youth from low-SES families, the group at greater statistical risk for less math progress? Do students from underrepresented racial and ethnic groups and low-SES families face additional risks of not progressing in math? For the first time, using a large, nationally-representative sample, we can answer these questions (see Chapter IV).

How Do School Contexts and Classroom Contexts Weaken or Strengthen Mindset Associations?

Mindset × Context Theory has mostly focused on the complementarity between individuals and their contexts to answer questions of whether supportive contexts make for a *stronger* association between a mindset and an outcome. This framing comes from the experimental history of Mindset × Context, which focused on understanding where a potentially beneficial intervention had its greatest benefits. As a result, Mindset × Context Theory has not examined the corollary of the complementary discussed above—the possibility that in the least-supportive contexts, the harm caused by a negative mindset would be greatest, which is also called an "accumulated disadvantage" or "double-jeopardy" effect. For example, are the achievement-undermining effects of low expectations most pronounced in high-stereotyping contexts? Indeed, as mentioned in Chapter I, a stereotype about a group can be thought of as a cultural expectation about that group's potential to succeed, which might undermine an adolescent's own internalized expectations for success. In the NSLM we focused on students' perceptions of gendered stereotypes in the classroom. Because stereotypes about ability in math tend to be negative for girls (e.g., Miller et al., 2015; Nosek et al., 2009; Zhao et al., 2022), we expected that girls with low expectations for success in math would be most negatively affected by the negative stereotyping environment. We did not have a priori hypotheses about the role of SES in this interaction, but we explored this possibility in accord with our interest in more complex identities (e.g., gender *and* SES rather than gender *or* SES).

In summary, if there is an "accumulated disadvantage" or "double-jeopardy" effect, presented by a negative mindset and a negative context, then the association between the mindset and the outcome would be stronger in the most unsupportive contexts. We examined this possibility in Chapters V and VI. Evidence of an accumulated disadvantage effect would widen the aperture of Mindset × Context Theory's predictions.

III. Analyzing the NSLM

The NSLM was designed to investigate questions about how educational contexts affect whether adolescents benefit from psychological resources such as their mindsets (Yeager et al., 2019). In this chapter, we describe the NSLM dataset and our approach to examining adolescents' progress in math during the transition to high school.

The NSLM Sample

The NSLM dataset was constructed using a probability sampling method with acceptable response rates, making it representative of 9th-grade students (those around age 15 experiencing their first year of secondary education) in regular U.S. public high schools. Analyses verified that the sample was representative with respect to a large number of observable characteristics, such as gender, race, ethnicity, English Language Learners (ELLs), free or reduced price lunch, poverty, food stamps, neighborhood income and labor market participation, and school curricular opportunities (Gopalan & Tipton, 2018). During the first few weeks of the 2015–2016 school year, students answered survey questions about their expectations, beliefs, and behaviors prior to taking part in a randomized controlled trial for a growth mindset intervention. (None of the predictor or moderator variables used in the present analyses were subject to treatment effects from the intervention; in addition, all analyses controlled for the growth mindset intervention variable). We supplemented the student survey with data collected on student grades and course-taking from school records.

The main analytical sample used in Chapters IV and V consisted of 9,971 students in 56 schools with valid measures for SES, gender, expectations, and 10th-grade math course-taking, when adolescents were around age 16. In Chapter VI, we limited our sample to students we could match to their 9th-grade math teachers, resulting in a sample of 6,856 students in 43 schools.

Table 1 describes the filters that resulted in these sample sizes. Most of the sample attrition was due to respondents' schools failing to provide us with their academic records. For 20 of our original sample schools, we only have partial course-taking records or none at all. In addition, 13 schools that provided us with course-taking records for 9th and 10th grades did not provide teacher information to facilitate matching them to students. We performed several analyses to understand whether this sample attrition biased our results and changed the claims we could make about

TABLE 1
Description of Analytic Samples

Sample Description	Sample Size Adolescents (Schools)	Explanation
Starting sample	16,138 (76)	Adolescents who participated in the time 1 survey and were assigned a survey weight.
Sample with math course-taking records	10,446 (56)	Excludes adolescents in schools that did not provide us with 9th- and 10th-grade course-taking records.
Sample with nonmissing values for expectations	10,423 (56)	Excludes respondents with item nonresponse to expectations.
Sample with nonmissing values for gender, parents' education and race	10,372 (56)	Excludes respondents with item nonresponse for gender, parents' education and race that we could not impute using school records.
	Analytic Sample for Chapters IV and V	
Sample with adolescents who started 9th grade in a math course level below advanced math	9,971 (56)	Excludes adolescents who started 9th grade in Algebra II or above in schools with traditional course pathways. Includes students who took Algebra II in schools that order Geometry after Algebra II ($n = 229$).
	Analytic Sample for Chapter VI	
Sample of adolescents matched to teachers	7,402 (48)	Excludes students within the eight schools did not provide us with teachers' names in their school records.
Sample of adolescents whose math teacher at the time of the survey can be confirmed	6,856 (43)	Excludes students within the five schools that did not give us grade records for 9th grade, which we used to connect students to the teacher they had at the time of the survey. For some students, we had write-in responses to teacher names we could connect to their school records.

representativeness. First, we compared the schools in the analytic samples to schools in the sampling frame (all U.S. 9th-grade public schools) using publicly available data, including the Common Core of Data (CCD), the Office of Civil Rights (OCR), and a district-level tabulation of American Community Survey (ACS) data (see Gopalan & Tipton, 2018 for more details). We did not find any significant differences between characteristics of schools in the analytic samples as compared to the schools in the sampling frame (see online Supporting Information: Table 1).

Second, we calculated the generalizability index (Tipton, 2014), a summary measure that provides the degree of distributional similarity between the schools in the analytic sample and the inference population, conditional on a set of covariates. The index is calculated using propensity scores from a sampling propensity score model, which predicts membership in the analytic sample, given a set of observed school-level characteristics, using logistic regression. The generalizability index takes on values between 0 and 1, where a value of 0 means that the analytic sample and inference population are completely different and a value of 1 means that the analytic sample is an exact miniature of the inference population on the selected covariates (see Tipton, 2014 for more details). The generalizability index is 0.96 for the main analytic sample and 0.97 for the secondary sample (see online Supporting Information: Table 2 for more details on the method and a description of the variables included in the propensity score), suggesting that the analytic samples in this monograph are as good as random samples from the population of interest with respect to the available school characteristics data. In addition, we examined where there were individual-level differences between the original NSLM sample and our two analytic samples. Importantly, we found that the distribution of gender, parents' education, math course-taking, race/ethnicity, and expectations for success in math did not differ significantly across these samples (see online Supporting Information: Table 3 for more details). In all, we found that site-level nonresponse did not compromise the generalizability of the results with respect to observables.

One unique feature of the NSLM dataset is that it included an adequate number of students within schools to facilitate analyses on gender and family SES intersectional groups as well as school and classroom peer norms. For most of the schools in the sample, we collected information from a full census of 9th-grade students (except for 12 of the larger schools in our dataset, in which we collected a random sample of about half of the 9th-grade students in the school). Many nationally representative surveys on education (such as the High School Longitudinal Study, Ingels et al., 2015) only surveyed a small random subsample of 20–30 students in each school. This would have prevented researchers from answering our research questions effectively. Given that our focus was on between-school achievement and peer norms and within-school intersectional gaps in math progress, this complete sampling of students in the NSLM was critical for statistical power. The complete sample also gave us a broader picture of a school's course-taking patterns, so that we could determine the normative pathway from 9th- to 10th-grade math and identify which students did not progress along it.

Despite these strengths of the NSLM data, as noted previously, a limitation is it did not afford robust examinations of racial and ethnic intersectionality with gender and SES, with respect to between-school moderators. There were three issues. First, racial and ethnic diversity across schools was not sufficient to ascertain racial and ethnic differences in math progress and expectations for success in math within schools and classrooms. A history of residential segregation in the United States means that schools are effectively racially segregated; over 40% of Black and Hispanic/Latinx students are in schools where 90–100% of students are from their own racial group (McGrew, 2019). Given this history, and the fact that the NSLM purposely sampled schools with a high percentage of students from underrepresented racial and ethnic groups (URG)—including Black, Hispanic/Latinx, and Native American students—, we were underpowered to perform analyses to determine how adolescents' expectations for success in math may predict academic progress in math differently by race and ethnicity *within* the same school context. Second, our focus was on gendered patterns of socioeconomic stratification. Within SES categories, racial and ethnic variation is lower than gender variation. Less than 10% of adolescents in the sample from URG were also from high-SES families. Within SES categories, the gender split was roughly 50/50, providing more statistical power for studying intersectional gender by SES identity groups. Third, analyses (presented in Chapter IV) revealed disparities in math progress by race and ethnicity, as expected given historical and ongoing neighborhood segregation, but the overall pattern for gender and SES was similar across groups—albeit somewhat magnified for students from underrepresented racial and ethnic groups.

Measurement

Outcome: Math Progress From 9th to 10th Grade

Defining the Outcome

The primary outcome was math progress, defined as whether adolescents advanced to a higher-level math course in 10th grade, which was our indicator of successful math progress. Adolescents who started high school in more advanced courses, such as Geometry, are better positioned to complete college-level math courses, including courses in precalculus or above, by the time they graduate. Adolescents who began high school in Algebra 1 can reach precalculus by the time they graduate, but only if they advanced to a higher level of math each year and did not opt out of math later in high school. Indeed, Figures 2 and 3 (Chapter I) showed a great deal of variation in course-taking sequences that was highly consequential for long-term educational outcomes.

Accounting for Variation

Math progress was defined locally for a given school, to account for differences in math course-taking patterns across students, schools, districts, and states, and differences in course-taking opportunities available to students. These differences in course-taking patterns across high schools can

TABLE 2
CROSS-TAB OF MATH COURSES TAKEN IN 9TH AND 10TH GRADES IN THE ANALYTIC SAMPLE

		10th Grade			
		Below Algebra	Algebra 1	Geometry	Algebra 2 or above
9th Grade	Below Algebra	0.61%	2.64%	0.54%	0.00%
	Algebra 1	0.79%	10.11%	55.42%	3.78%
	Geometry	0.19%	0.09%	0.33%	23.20%
	Algebra 2 or above	0.02%	0.05%	2.20%	0.03%

Note. $N = 9{,}971$. Excludes adolescents who took advanced math in 9th grade.

complicate the association between the levels of coursework that students took in 9th and 10th grades. Table 2 displays the pathways from 9th to 10th grade in the sample, with each cell representing the total percent of students who made that particular transition. The majority (55.42%) started in Algebra 1 in 9th grade and transitioned to Geometry in 10th grade. Another 23.20% started in Geometry in 9th grade and transitioned to Algebra 2 in 10th grade. The next largest cell includes students who did not progress in math; 10.11% of our sample remained in Algebra 1 between 9th and 10th grade. Recall that, by and large, these students were "Off track" and went on to worse educational outcomes (Figure 3 in Chapter I).

We consider the math course level at which students started and the within school math course trajectories to isolate students' individual progress from the school structures that determine their options. Consequently, we measured the number of math levels students advanced between 9th and 10th grades (around ages 15–16), based on students' course-taking records from their schools.

Coding the Outcome

A third-party firm coded students' 9th- and 10th-grade math courses to the same standard using the School Courses for the Exchange of Data (SCED) classification, which is considered the gold-standard in population studies of curricular differentiation (National Forum on Education Statistics, 2014). We further grouped these courses into hierarchical levels of math course-taking that match the lock-step sequence of mathematics: Below Algebra (1), Algebra 1 (2), Geometry (3), Algebra 2 (4), Precalculus (5), Other advanced math (6), and Calculus (7). We determined students' math progress by subtracting the level of their 9th-grade math course from the level of their 10th-grade math course.

Although most schools follow this typical hierarchical ordering of math course-taking, some schools do not. Some schools include other courses, such as integrated math courses that combine topics from Algebra 1 and Geometry, or they switch the order of courses, such as having students take Algebra 2 before Geometry. Comparing within-school course-taking patterns across all 56 sample schools revealed nine schools that did not appear to follow this hierarchical order. In each case, these schools' patterns were confirmed by inspecting the course catalogs. In those schools, the order of Geometry and Algebra 1 or Algebra 2 was switched to match the schools' course-taking structure. Thus, for students in these schools, we coded their math progress to match the normative structure of their school (i.e., students who took Algebra 2 in 9th grade and Geometry in 10th grade were coded as 1 instead of −1).

The distribution of math progress is in Table 3. A 0 indicates that a student stayed in the same level of math and a 1 indicates that a student advanced a full level ($M = 0.89$, $SD = 0.43$). Given the skewed distribution, we winsorized this variable in analyses with a range of −1 to 2 to ensure that outlier course-taking patterns do not affect our results.

Why do Students Fail to Show Adequate Progress?

There are a few reasons why a student may not progress in math during the transition to high school. First, the student may fail their 9th-grade math course. Indeed, about half of the students in the sample who did not progress in math between 9th and 10th grades received a failing grade in their 9th-grade math course. Second, the student may have failed a state test given at the end of 9th grade in Algebra 1 (there is not a similar examination for Geometry in most states). In these cases, the school may require the student to retake Algebra 1 to be able to pass the test the following year. Third, the student may fall off the college-preparatory math pathway in high school. Although many states require students to take 3–4 years of math, the level of math taken is not specified. Students may be diverted into vocational math courses that no longer prepare them for college entry, for instance, if the school no longer considers the student to be college material. We focus on math progression overall, rather than narrower measures such as getting a failing course grade, to capture the different potential ways students get off track in math during the transition to high school.

TABLE 3

Distribution of the Outcome Variable: Progress in Math From 9th to 10th Grade

Change in Math Course Levels from 9th to 10th Grade	%	*n*
−2	0.21	21
−1	0.66	66
0	11.38	1,135
1	85.19	8,494
2	2.38	237
3	0.18	18
Total	100.00	9,971

Note. Analytic sample includes students with valid measures of expectations, gender, and parents' education and excludes students who took advanced math in 9th grade (see Table 1).

Measurement of Independent Variables

Intersectional SES and Gender Identity Groups

This monograph focuses on understanding whether expectations for success in math are a resource that applies equally to adolescents' math progress across student groups and school and classroom contexts. As discussed in prior chapters, stratification in math progress by gender and SES is particularly apparent. We examined the intersectional interplay of gender and SES by separating adolescents into four categories: boys from high-SES families, girls from high-SES families, boys from low-SES families, and girls from low-SES families.

SES

We use mother's education as a proxy for SES for both theoretical and methodological reasons. Mother's education is particularly relevant for questions about how students interact with their educational contexts, given that college-educated parents are potentially more knowledgeable about the importance of advanced course-taking for college-entry and are better situated to ensure their children are receiving the best educational opportunities (Crosnoe & Schneider, 2010). Another frequent indicator of SES in educational research—free/reduced lunch status—was only provided by a subsample of schools. Destin and colleagues (2019) compared these two measures of SES using NSLM and found they were correlated and led to similar predictions. Among students whose school reported that they received free or reduced lunch, 84% reported their mother did not receive a bachelor's degree.

We consider adolescents who reported that their mothers had earned a bachelor's degree or above to come from a high-SES family, whereas adolescents who reported that their mothers earned below bachelor's degree or that they did not know their mothers' education level were considered to come from a low-SES family (Destin et al., 2019). For adolescents who did not respond to this question, we imputed family SES from school records. Adolescents who received free or reduced lunch were imputed as low-SES, and those who did not were imputed as high-SES.

Gender

The indicator of gender from the 9th-grade student survey asked students to select whether they were boys or girls. We imputed nonresponses to this self-reported question from school administrative records, which were available for all students and match self-reports with 99% accuracy. One limitation of this work is that the survey did not offer opportunities for students to have nonbinary gender identities, so we can speak only to adolescents who identify as a boy or a girl.

Intersectionality

Investigating gender by SES intersectional groups helps to shed light on inequality in math progress. Figure 4 presents the proportion of adolescents from each group that did not progress in math from 9th to 10th grades, showing large gaps in math progress. Girls from high-SES families progressed in math between 9th and 10th grades at the highest rates; less than 5% of these adolescents were off track. Boys from high-SES families were about twice as likely to be off track in math as girls from high-SES families; still, fewer than 10% of them failed to progress. Among adolescents from low-SES families, about 20% of boys and 13% of girls were off track. Thus, the off-track rate for boys from low-SES families was 300% greater than it was for girls from high-SES families. Within these SES gaps, there are important gender differences to consider, and vice versa. We examined whether these gaps persisted among adolescents with similar expectations in similar educational contexts.

Expectations for Success in High School Math

The main independent variable, mindset, was operationalized as adolescents' expectations for success in math during high school, which they reported early in their 9th-grade year. Note that this variable is different from the expectations questions that are typically asked in sociological research; those items ask about how far in their educational careers students expect to go (e.g., to college, to a Ph.D.). College-going expectations, however, would not necessarily pinpoint students' expectations in math, because students are not fully aware of the importance of the math curriculum for

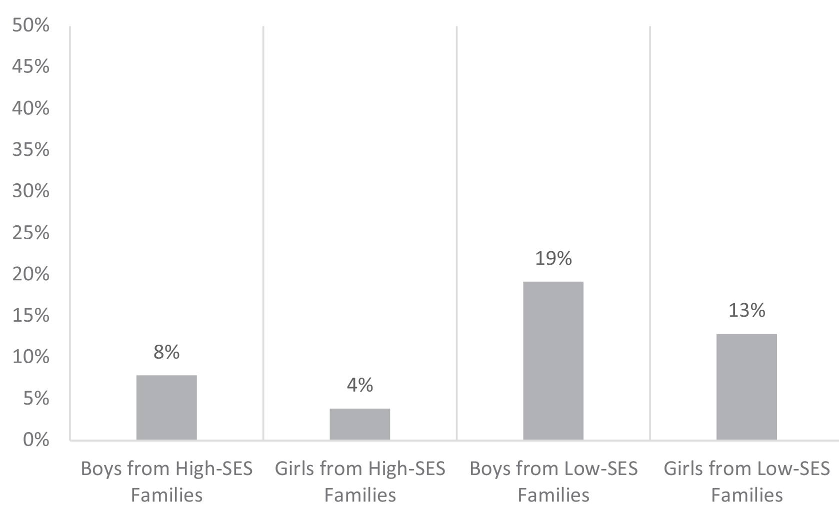

Figure 4.—Percentages of adolescents off track by intersectional gender and SES identity groups. $N = 9{,}971$. Off-track students are those who repeated the same course level or decreased course levels between 9th and 10th grades. SES = socioeconomic status.

later postsecondary success. Further, our interest here was in students' mindsets about their abilities, in their contexts, which is more closely aligned with the expectations typically measured in expectancy-value theory (Eccles & Wigfield, 2020).

Expectations Item

The NSLM question was written by a panel of psychological advisors to the NSLM to elicit students' expectations for success in the broader context of their academic self-concept and perceptions of math course difficulty: "Thinking about your skills and the difficulty of your classes, how well do you think you'll do in math in high school?" (1 = *extremely poorly*, 7 = *extremely well*, $M = 5.25$, $SD = 1.14$). Figure 5 shows the overall distribution of expectations for success in math. The majority of adolescents reported that they expected to do *somewhat well* or *very well*; very few respondents expected to do *extremely poorly* and *very poorly*.

This measure was designed to capture how expectations for success in math differ across adolescents in different contexts, but with a single, easy-to-interpret item that was inspired by a validated instrument used in previous research (Hulleman & Harackiewicz, 2009; "Considering the difficulty of this course and my skills, I think I will do well in this class"). Hulleman and Harackiewicz's item was revised to fit the focus of the present study (1) on math and (2) on assessing expectations about performance in high school math more generally rather than in a particular course. Similar to other validated items of expectancies or self-efficacy (e.g., "How well do you expect to do in math this year?"; Wigfield &

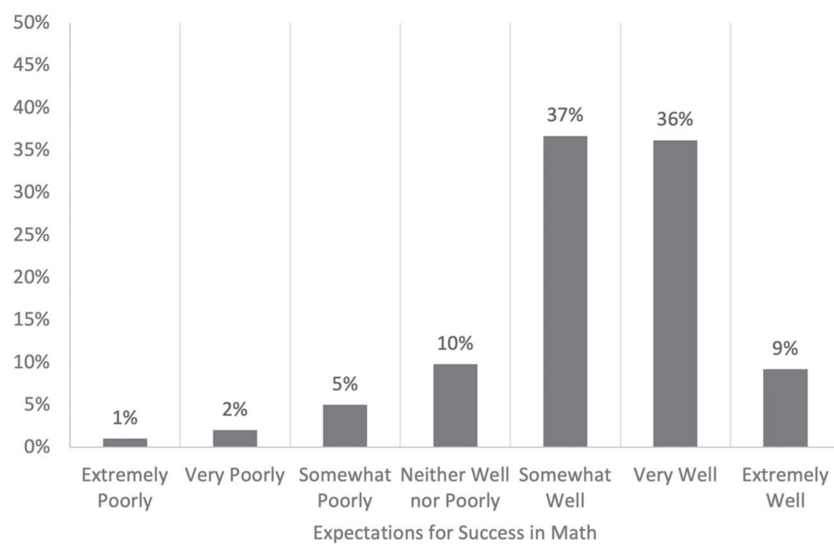

FIGURE 5.—Distribution of adolescents' 9th grade expectations for success in high school math. $N = 9{,}971$. The percent of adolescents who reported expecting to do *Extremely Poorly* (1) to *Extremely Well* (7).

Eccles, 2000), our item assessed students' confidence that they would be able to perform a particular academic task successfully (in this case, high school math). The item also asked students to factor their skills and the difficulty of their courses into their responses; this was done to clarify the point of comparison for their judgment, in an attempt to reduce measurement error. Of note, the expectations item did not ask students to compare themselves to other students in their class, because that relative comparison was not core to our conceptualization of expectations for success in math. In addition, this measure of expectations asked students to focus on their success in high school math in particular, which is more relevant to study inequality in math progress, rather than on their aspirations for educational progress in general (e.g., college-going intentions, which are more commonly studied in sociology, Schneider & Stevenson, 1999).

Assessing the Impact of a Single Item Measure

One possible limitation of this monograph is its use of a single item, because single items can be unreliable. To assess the test–retest reliability of the NSLM item, we compared adolescents' reports of their expectations from time 1 (early in high school) and time 2 (a few weeks or months later). Among the subsample of students for whom we have expectations measured in the same way on both surveys ($n = 4{,}529$), these measures were positively correlated ($r = .60$, $p < .001$). Criterion validity is shown in correlations between expectations and related psychological constructs (see Table 7, discussed in Chapter IV). Of note, we reconducted all analyses when using a composite of the expectations measured at two time points (which reduces sample size but improves reliability), and we found the same results. This evidence suggested that the single-item measure was adequate for our purposes.

Ninth-Grade Math Level

A key source of stratification in high school math course-taking was whether students took Algebra 1 in 8th or 9th grade, because it determined whether they started high school in Geometry or not. The majority of 9th-grade students begin high school in Algebra 1 or below, but some, often more advantaged students, begin high school in Geometry or above (74% vs. 26%, respectively). Our primary outcome variable was whether adolescents made progress in math, regardless of where they began, but we also considered math level as a moderator. That is, we assessed whether their likelihood of advancing, as well as the relationship between their expectations and advancement, differed by their math position at the start of high school—in Algebra 1 or below versus in Geometry or above.

Covariates

Race/ethnicity

In the NSLM survey, students were asked to report all of the racial and ethnic groups with which they identified. We categorize students similar to conventions within the U.S. Census to indicate whether students identified as Black, Hispanic/Latinx (non-Black), Native American, White (non-Hispanic), and Other Racial or Ethnic group (including students who identified as Asian or Middle Eastern).

We examined a third layer of potential inequality, race, and ethnicity, in supplemental analyses to capture a broader picture of intersectional gaps in math progress. As noted above, due to data limitations, we examined only whether the relationship between expectations for success in math and math progress differed between students from underrepresented racial and ethnic groups (URG) and students from the White, non-Hispanic group in these supplemental materials. We acknowledge that there are limitations in grouping students in this manner, especially in combining Black, Hispanic/Latinx, and Native American students. Although students from these backgrounds have unique experiences in schools, they do share the experience of historic exclusion from White-dominated schools. Since the mid-1960's, the United States has been concerned specifically with narrowing disparities in educational outcomes and resources between URG students and non-Hispanic White students, to address this history of legalized segregation. In addition, we excluded students from Asian or Middle Eastern backgrounds only in the analyses of intersectional racial and ethnicity differences because there is some evidence the schools in the NSLM sample do not have a representative share of students from these backgrounds. Thus, another limitation of our study is that we cannot speak to the potentially different experiences of Asian or Middle Eastern students.

Although there was some racial and ethnic diversity among adolescents from high- and low-SES families, the cell sizes were too small to perform high-level analyses. Table 4 displays the means, standard deviations, and percentages of the main analytical variables by Gender × SES intersectional groups. Among adolescents from high-SES families, around 66% were non-Hispanic White, 13% were Black, and 10% were Hispanic/Latinx. Among adolescents from low-SES families, around 43% were White, 18% were Black, and 29% were Hispanic/Latinx. Black and Hispanic/Latinx students were overrepresented among students from low-SES families, but the variation in race and ethnicity among students from high-SES families suggests that gaps in math progress in SES cannot be attributed solely to racial and ethnic identity (and racial and ethnic gaps cannot be attributed solely to family SES).

Prior Achievement

Average math grades in 8th grade indicate students' grade point average (GPA) as reported in their transcripts (range = 0–4.3, $M = 2.93$, $SD = 1.02$).

TABLE 4

MEANS AND PERCENTAGES FOR MAIN ANALYTIC VARIABLES BY GENDER AND SES GROUPS

	Boys from High-SES Families		Girls from High-SES Families		Boys from Low-SES Families		Girls from Low-SES Families	
	M/%	*SD*	*M*/%	*SD*	*M*/%	*SD*	*M*/%	*SD*
Expectations for success in math	5.46	1.06	5.34	1.05	5.15	1.17	5.06	1.15
Math progress	0.95	0.37	1.00	0.30	0.81	0.48	0.88	0.45
Eighth grade GPA	3.12	0.77	3.43	0.67	2.59	0.90	3.00	0.82
Took geometry or above in 9th grade	37.86%		39.59%		17.07%		20.32%	
Race/ethnicity								
non-Hispanic White students	64.50%		67.33%		42.04%		42.01%	
Students from underrepresented groups	28.45%		24.53%		50.00%		51.37%	
Students from other racial/ethnic groups	7.05%		8.14%		7.96%		6.62%	
n	1,849		1,834		3,122		3,169	

Note. Students from underrepresented groups include those who identified as Black, Hispanic/Latinx, and Native American. The "Other" category includes Asian, Middle Eastern, and students who selected "Other" race.
M = mean; SD = standard deviation.

We had information about 8th-grade math GPAs only for a subsample of students ($n = 5{,}661$). We used the dummy variable technique to indicate missingness on this variable (as described in more detail below), but conducting multiple imputation yielded similar results.

Psychological Measures

We examined other measures of students' mindsets and their orientations toward school, to control for potential confounding in the link between expectations for success in math and math progress. We used these measures in analyses reported in Chapter IV to understand which of them were strongly related to expectations for success in math and we included those in our models. The single-item measures were: *Math Interest* ("In your opinion, how interesting is the subject of math in high school?" [1 = *not at all interesting*, 5 = *extremely interesting*, $M = 2.66$, $SD = 1.12$]); *Academic Stress* ("In the last few weeks, how often did you feel overwhelmed or stressed out about your classes in high school?" [1 = *never*, 5 = *very often*, $M = 3.10$, $SD = 1.15$]); *Belonging Uncertainty* ("When you think about your high school in general, how often, if ever do you wonder: Maybe I don't belong here?" [1 = *never*, 5 = *very often*, $M = 2.07$, $SD = 1.10$]); and *Trust in Math Teacher* ("I trust my math teacher." [1 = *not at all true*, 5 = *extremely true*, $M = 3.65$, $SD = 1.11$]). We also measured *Fixed Mindset Beliefs*, which was the unweighted average of responses from three questions assessing whether students perceive that one's abilities are malleable and can be changed by effort and learning or are fixed and cannot be changed ("You have a certain amount of intelligence, and you really can't do much to change it," "Your intelligence is something about you that you can't change very much," and "Being a math person or not is something you really can't change. Some people are good at math and other people aren't." [1 = *strongly disagree*, 6 = *strongly agree*]). We combined these items into a scale, where higher values indicated more fixed mindset beliefs ($M = 3.03$, $SD = 1.14$).

Note that we focused on expectations for success in math rather than other psychological measures, because expectations for success in math was a more general construct that was more strongly linked to math progress in 10th grade than the other individual mindset measures on their own, as shown in Table 5. The strength of this overall association provided an informative opportunity to interrogate the identity groups and contexts in which it was weaker or stronger.

Missing Data

Missing values for covariates only (not for primary predictors of interest) were accounted for using the dummy variable adjustment technique (Allison, 2001), where we replaced missing values with the sample mean and the models included a dummy variable indicating whether imputation was done. Therefore, no listwise deletion for missing covariates was conducted.

TABLE 5

Correlations Between Math Progress and Psychological Measures in 9th Grade

Psychological Measures	Zero-Order Correlation with Math Progress	*N*
Expectations for success in math	.20	9,971
Fixed mindset beliefs	−.10	9,968
Math interest	.07	9,964
Belonging uncertainty	−.07	9,951
Trust in math teacher	.06	9,916
Academic stress	−.02	9,946

Note. This table excludes students who had item nonresponse for a given measure. In regression models in the paper, however, item missingness was addressed through the missing data dummy technique.

Analytical Plan

Each of the next three analytical chapters considered different aspects of one question: How do adolescents' expectations for success in math relate to their math progress across intersectional SES and gender groups? We preview the analyses here, but each chapter goes into its own methods in more depth. In every chapter, we applied sample survey weights, so that the findings were representative of 9th graders in U.S. public schools.

Chapter IV examined which factors are related to expectations for success in math during the transition to high school and differences in expectations for success in math and math progress by intersectional SES and gender groups. We also conducted exploratory analyses by race and ethnicity. We estimated the association between expectations for success in math and math progress in school in a multilevel BCF model to isolate this link within schools from variation in the structure of the math curriculum between schools. We focused on the interaction between adolescents' expectations for success in math and their gender and SES background in our main models. In supplemental analyses, we also examined how membership in an URG related to these associations.

Chapter V investigated how educational contexts were related to whether adolescents benefitted from their expectations for success in math. Specifically, we examined the Chapter IV interactions in different formal and informal school contexts: Did expectations for success in math matter differently for students' math progress in schools with different formal resources—the historical achievement of the student body—and schools with different informal resources—the peer learning norms of the school community?

Chapter VI probed more deeply into adolescents' learning contexts to understand how the culture of their classrooms related to whether and how their expectations for success in math translated into math progress. Using a large subsample of students paired to their 9th-grade math teachers, we measured perceived classroom gender stereotyping—that is, the degree to which adolescents felt that, within their math class, "people's judgment of you will be affected by your gender"—and used this variable as a moderator of the relation between expectations for success in math and progress in math.

BCF Modeling

All results presented in Chapters IV and V come from one, multi-level BCF model fit, with students nested within schools. All analyses in Chapter VI come from another multi-level BCF model fit, with students nested within teachers. BCF is an established method for approaching causal inferences from nonrandomized variables while also detecting true sources of effect heterogeneity—that is, differences in the predictive effect of a variable across subgroups or contexts—without lending much credence to noise (Hahn et al., 2020; McConnell & Lindner, 2019; Wendling et al., 2018). Therefore, it is well-suited for the present analyses, or perhaps for any test of ecological models of development.

Benefits of the BCF Approach

There are three primary reasons why the BCF model provides significant advantages over traditional linear regression modeling. First, *BCF can account for confounding* in the effect of expectations for success in math on the outcome, and math progress. As we show in Chapter IV, expectations for success in math were correlated with many other psychological variables (e.g., belonging uncertainty or fixed mindset). To isolate the contribution of expectations for success in math above and beyond these other variables, BCF incorporates a propensity score. This allows the BCF model to identify the partial effect of expectations. If we assume that all possible confounds in the link between expectations and math progress are in the propensity score, then BCF will identify a true causal effect of expectations. Note that in this case, we do not need to make this assumption because we are not making strong causal claims. Regardless, the inclusion of the propensity score yields significant improvements in isolating the expectations effect, as shown in many past simulation studies evaluating the BCF method (Dorie et al., 2019; Hahn et al., 2018).

Second, *BCF can detect complex, higher-order interactions*, without over-interpreting random variation. It can assess how expectations for success in math have different effects across race/ethnicity, gender, SES, math level (Algebra I vs. Geometry), school achievement, and peer norms groups; that is, BCF can detect seven-way interaction effects, without any increase in the risk of false positive findings. The reason why is BCF's use of the popular Bayesian Additive Regression Trees (BART) (Chipman et al., 2010) approach, which is a machine-learning approach that has been a top performer in empirical evaluations of methods for causal inference (Dorie et al., 2019; Hahn et al., 2019; McConnell & Lindner, 2019; Wendling et al., 2018), along with conservative prior distributions that "shrink to homogeneity." This means that the algorithm strongly penalizes the model against finding outlying subgroups, but if they are reliably there, they can shift the model's conclusions accordingly. Further, BCF avoids one of the key issues with typical applications of the BART algorithm: the regularization applied to the treatment effects is difficult to characterize and depends on nuisances like the number of control variables in the model. BCF avoids this by implementing separate regularization (i.e., shrinkage) for the covariate part of the model and the moderator part of the model (Hahn et al., 2019). The result is that BCF can both isolate the partial effects of an observed variable (in this case, expectations for success in math, conditional on covariates), while also separately modeling the moderators fully.

Third, because BCF is a fully Bayesian method, then it can use the array of tools available to summarize the posterior distribution without increasing the risk for false conclusions. In a typical regression approach, the model must be refit many times, with different centering choices to get different simple effects estimated, and with different (arbitrary) choices about which groups are compared to which. By contrast, with BCF, the data are used once: to move from the prior distribution to the posterior distribution. Then, the algorithm draws from the posterior distribution using Markov chain Monte Carlo (MCMC) methods (Chipman et al., 2010; Hahn et al., 2020; Hill et al., 2020; Starling, Murray, Lohr, et al., 2020). Rather than outputting a regression coefficient, like in a linear regression analysis, the model output is large matrices of draws from the posterior distribution, with thousands of draws for each individual person in the dataset, and it is these draws that are then summarized to produce all conclusions. This facilitates honest Bayesian inference concerning subgroup effects and subgroup differences and eliminates concerns with multiple hypothesis testing that can threaten the validity of a frequentist p value (Woody et al., 2021).

Model Parameters

The BCF model is specified as

$$y_{ij} = \alpha_j + \beta(x_{ij}, \hat{\pi}_{ij}) + \tau(w_{ij}) \cdot z_i + \epsilon_{ij},$$

where y_{ij} is the outcome for student i in school j and z_i is expectations for success in math. Here x is a vector of covariates and w is subset of these which are potential effect moderators, and $\hat{\pi}_{ij}$ is a propensity score for each student's expectations for success in math, conditional on the measured covariates. These covariates may be measured at the individual level or the school level. We also allow for school-level intercept random effects, α_i, to account for varying levels and clustering. The individual-level error term ϵ_{ij} is assumed to be normally distributed with variance σ^2.

Here β and τ are nonparametric functions which allow for nonlinearities and interactions between covariates in affecting the expected outcome and treatment effects. This model specification is similar to traditional multilevel linear models of heterogeneous treatment effects, but relaxes the strict assumption of linearity and additivity between the covariates and the expected value of the outcome and conditional average treatment effects.

To complete our Bayesian model, we must specify prior distributions for the unknown parameters in the equations above. These include the nonparametric functions $\beta(\cdot)$ and $\tau(\cdot)$, the random effects α_i, and the error variance σ^2. The priors for the functions $\beta(\cdot)$ and $\tau(\cdot)$ are taken from the BCFs model (Hahn et al., 2020). Under this model, both functions have a sum-of-trees representation, as first defined for Bayesian methods in Chipman et al. (2010). Each tree consists of a set of internal decision nodes which partitions the covariate space, and a set a of terminal nodes, or leaves, corresponding to each element of the partition. The prior for each of $\beta(\cdot)$ and $\tau(\cdot)$ is comprised of three parts: the number of trees, two parameters controlling the depth of each tree, and a prior on the leaf parameters. Use of this sum-of-trees term allows for detection of nonlinearity and interactions between covariates.

A key feature of the BCF model is that the prior for $\tau(\cdot)$, which captures heterogeneity in a "treatment" effect (the partial effect of expectations), is regularized more heavily compared to the control function $\beta(\cdot)$ in order to shrink toward homogeneous effects, that is, that the "treatment" effect is constant across all values of the moderators. The prior for $\tau(\cdot)$ uses fewer trees, with each tree being regularized to be shallower (i.e., contain fewer partitions). Details on prior specification are specified in several technical papers (Chipman et al., 2010; Hahn et al., 2020; Starling, Murray, Carvalho, et al., 2020; Starling, Murray, Lohr, et al., 2020). The random effect α_i is given a Gaussian prior with the standard deviation having a prior of a half t-distribution with 3-degrees of freedom, as recommended by Gelman (2006). Finally, the error variance is given an inverse χ^2 prior with 3-degrees of freedom and scale parameter informed by the data.

Propensity Score

Propensity scores were estimated in a separate random forest model (using the *randomForest* package in R, Liaw et al., 2015). The obtained score was then used in the primary BCF model. The random forest model predicted the "treatment" variable (i.e., expectations for success in math) with all of the covariates in the main model (parental education, gender, race and ethnicity, 9th grade math level, 8th grade math GPA, and psychological variables: interest, stress, belonging uncertainty, trust, and growth mindset). The resulting final propensity score was each participant's fitted value from this model.

IV. Intersectional Differences in Adolescents' High School Math Development

In this chapter, we investigated the link between adolescents' expectations for success in math early in high school and their math progress in 10th grade to understand whether and for whom these expectations are related to math progress. We expected that expectations for success in math would be related to math progress for all adolescents. What we wanted to know was the magnitude of this association among boys and girls from high- and low-SES families, and whether disparities in outcomes across gender by SES intersectional groups were narrowed or widened among students with high versus low expectations, respectively.

Intersectional Differences in Expectations for Success in High School Math

As a preliminary matter, we started by examining differences in adolescents' expectations for success in math across gender, SES, and race and ethnicity and what factors related to these expectations. Here we refer to Black, Hispanic/Latinx, or Native American students as students from underrepresented groups (URG) to acknowledge the societal inequalities that have historically led groups with these identities to be less represented in advanced math and science. For reasons explained earlier, we did not have the sample size to generalize to multiple specific underrepresented identity groups. Also recall that due to the small sample size of Asian and Middle Eastern students in this study, and the large amount of diversity within that group, we concluded that results comparing Asian and Middle Eastern students to other groups would not be generalizable. Therefore, although Asian and Middle Eastern students are included when analyses are broken down only by gender and SES, they are not included in comparisons among racial and ethnic groups, which is an important limitation in our findings.

Table 6 shows differences in adolescents' expectations for success in high school math by gender, family SES, and race and ethnicity. On average, adolescents from high-SES families reported higher expectations for success in math than those from low-SES families, boys reported higher expectations than girls, and students categorized as non-Hispanic White reported higher expectations than students categorized as URG. Among adolescents from high-SES families, boys had significantly higher expectations than girls, but the expectations for boys and girls from low-SES families were not significantly different (Tables 6a and 6b).

TABLE 6a

Differences in Adolescents' Expectations for Success in Math by Gender and SES

Gender and SES Groups	*M*	*SD*	*95% CI*
Boys from high-SES families	$5.51^{b,c,d}$	1.06	[5.44, 5.57]
Girls from high-SES families	$5.40^{a,d,c}$	1.00	[5.34, 5.47]
Boys from low-SES families	$5.16^{a,b}$	1.18	[5.10, 5.22]
Girls from low-SES families	$5.08^{a,b}$	1.22	[5.02, 5.15]

Note. $N = 9{,}971$.
CI = confidence interval; *M* = mean; *SD* = standard deviation.
[a]Significant difference with boys from high-SES families.
[b]Significant difference with girls from high-SES families.
[c]Significant difference with boys from low-SES families.
[d]Significant difference with girls from low-SES families.

TABLE 6b

Differences in Adolescents' Expectations for Success in Math by Gender, SES, and Race/Ethnicity

Gender, SES, and Racial/Ethnic Groups	*M*	*SD*	*95% CI*	
Boys from high-SES families, non-Hispanic White group	$5.55^{b,c,d,e,f,g,h}$	0.98	5.47	5.63
Boys from high-SES families, underrepresented group	$5.36^{a,e,f,g,h}$	1.25	5.24	5.47
Girls from high-SES families, non-Hispanic White group	$5.43^{a,e,f,g,h}$	0.98	5.34	5.51
Girls from high-SES families, underrepresented group	$5.30^{a,f,h}$	1.08	5.18	5.41
Boys from low-SES families, non-Hispanic White group	$5.20^{a,b,c,f,h}$	1.08	5.12	5.29
Boys from low-SES families, underrepresented group	$5.08^{a,b,c,d,e,h}$	1.27	5.00	5.17
Girls from low-SES families, non-Hispanic White group	$5.18^{a,b,c,h}$	1.11	5.09	5.27
Girls from low-SES families, underrepresented group	$4.95^{a,b,c,d,e,f,g}$	1.32	4.86	5.04

Note. $N = 9{,}391$. Sample excludes students who did not identify as non-Hispanic White or from an underrepresented group (Black, Hispanic/Latinx, and Native American).
CI = confidence interval; *M* = mean; *SD* = standard deviation.
[a]Significant difference with boys from high-SES families, non-Hispanic White group.
[b]Significant difference with boys from high-SES families, underrepresented group.
[c]Significant difference with girls from high-SES families, non-Hispanic White group.
[d]Significant difference with girls from high-SES families, underrepresented group.
[e]Significant difference with boys from low-SES families, non-Hispanic White group.
[f]Significant difference with boys from low-SES families, underrepresented group.
[g]Significant difference with girls from low-SES families, non-Hispanic White group.
[h]Significant difference with girls from low-SES families, underrepresented group.

Diving into the different intersectional groups, boys categorized as non-Hispanic White from high-SES families reported significantly higher expectations for success in math than any other group. Girls categorized as URG from low-SES families reported significantly lower expectations for success in math than any other group. The disparity between these two intersectional groups was substantial: about half a standard deviation.

Differences in expectations for success in math were greater by SES than by gender, although gender differences remained. In fact, although mean levels of expectations differed, the distribution of expectations among boys and girls of the same SES group was very similar, as shown in Figure 6. Across all groups, few adolescents reported very low expectations for success in math, but boys and girls from low-SES families reported neutral or low expectations at almost twice the rate as boys and girls from high-SES families did (Figure 6). Interestingly, a similar percentage of girls from high-SES families and boys from low-SES families reported expecting to do "extremely well" in high school math (about 10%). Thus, although SES gaps in expectations were prominent, there were gender dynamics at play that were also important to consider.

Where Did Expectations for Success in Math Come From?

We also explored other factors that might contribute to how students formed their expectations for success in math and what they mean for development. Table 7 displays zero-order correlations between adolescents' expectations for success in math during the transition to high school and other measures related to their psychological resources in 9th grade.

On average, adolescents who reported feeling that they did not belong in their school, believed intelligence is fixed rather than malleable, and reported higher levels of academic stress reported lower expectations for success in high school math (Table 7). Adolescents who trusted their math teacher and had more interest in math on average reported higher expectations for success in math.

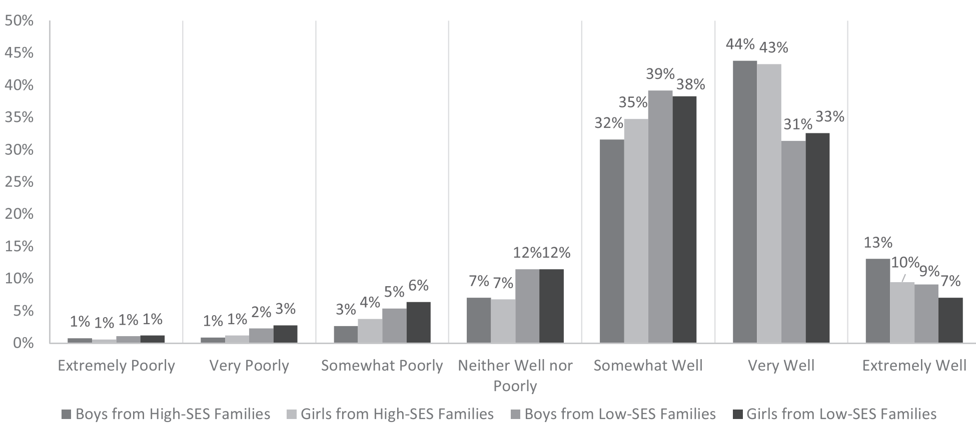

FIGURE 6.—Joint distribution of expectations for success in math by gender and SES. $N = 9{,}971$. Figure displays the weighted percentage of each group of adolescents that selected each category of expectations (1 = *Extremely Poorly* to 7 = *Extremely Well*).

TABLE 7
Understanding the Expectations for Success in Math Measure: Correlations With Other Psychological Variables in 9th Grade

Psychological Measures	Zero-order Correlation with Expectations	*N*
Math interest	.49	9,964
Trust in math teacher	.24	9,916
Belonging uncertainty	−.20	9,951
Fixed mindset beliefs	−.18	9,968
Academic stress	−.17	9,946

Note. This table excludes students who had item nonresponse for a given measure. In regression models in the paper, however, item missingness was addressed through the missing data dummy technique.

These correlations in Table 7 speak to how adolescents' backgrounds and learning contexts relate to their expectations. If they do not feel like they fit in their school community, do not feel respected by their math teacher, and are stressed by the amount of schoolwork they have to do, then they may have low expectations for their success in high school math. Their beliefs about the malleability of their intelligence and their level of interest in math may even reflect exposure to societal stereotypes about who can be, is, and should be successful in math.

One potentially confounding factor is adolescents' interest in math. This item, among the factors we examined, had the strongest correlation with expectations for success in math. Expectancy-value theory suggests that adolescents' expectations and interest in math are both strong, proximal determinants of their achievement-related decisions and behaviors (Eccles & Wigfield, 2002, 2020). We examined differences in math interest by adolescent groups (Table 8) to understand the role it may play in gaps in math progress. Boys from high-SES families had the most interest in math, and girls from low-SES families had the lowest, similar to the pattern for expectations. Unlike expectations for success in math, math interest did not differ by family background; girls from high- and low-SES families had similar levels of math interest, as did boys from high- and low-SES families.

TABLE 8
Differences in Adolescents' Math Interest by Gender and Family SES

Gender and SES Groups	*M (SD)*	*SD*	*95% CI*
Boys from high-SES families	2.75[b,c]	1.14	[2.67, 2.82]
Girls from high-SES families	2.60[a]	1.08	[2.53, 2.68]
Boys from low-SES families	2.66	1.14	[2.60, 2.72]
Girls from low-SES families	2.59[a]	1.11	[2.53, 2.64]

Note. $N = 9{,}964$, excluding students who had item nonresponse for math interest. We do not find any significant differences between boys from low-SES families and any other group.
CI = confidence interval; *M* = Mean; *SD* = standard deviation.
[a]Significant difference with boys from high-SES families.
[b]Significant difference with girls from high-SES families.
[c]Significant difference with girls from low-SES families.

Among adolescents from high-SES families, boys had greater math interest than girls. We did not find the same difference among adolescent boys and girls from low-SES families. Differences in math interest, therefore, were not sufficient to explain disparities in math progress.

Another important factor to consider was adolescents' math position at the start of high school. (We display the distribution of expectations by gender/SES groups and math level in online Supporting Information: Figures 1 and 2). The expectations question, as stated in Chapter III, asked adolescents to consider the difficulty of their courses when determining their expectations for success in math. This could suggest that adolescents in more challenging math courses would report lower expectations for success in math than those in lower-level courses. In fact, we found the opposite. As Table 9 shows, adolescent boys and girls from both high- and low-SES families reported higher expectations for success in math when they started high school in more advanced math courses. Note that adolescents from low-SES families were overrepresented among the students who began math in Algebra 1 or below in 9th grade. Adolescents in Geometry or above may know they are better positioned to succeed in high school math because they are in a more advanced math course than their peers, which signals higher expectations for success in math from the school community. Yet, within 9th-grade course levels, significant differences in expectations for success in math across SES and gender groups remained. Among students in Algebra 1 or below, adolescents from low-SES families reported lower expectations for success in math than those in high-SES families, and girls from low-SES families reported even lower expectations than boys from low-SES families. We found a similar SES pattern among students in Geometry and above, but girls from high-SES families also reported lower expectations than boys from high-SES families, consistent with past studies of high-achieving girls (Riegle-Crumb & Morton, 2017).

TABLE 9

Average Expectations for Success in Math by 9th Grade Math Course Level, Gender and Socioeconomic Background

Gender and SES Groups	*M*	*SD*	*95% CI*	*% of Subsample*	*N*
Algebra 1 or below					
Boys from high-SES families	5.30	1.08	[5.22, 5.39]	15.58	1,148
Girls from high-SES families	5.23	1.03	[5.14, 5.32]	15.04	1,108
Boys from low-SES families	5.04	1.17	[4.98, 5.10]	35.11	2,587
Girls from low-SES families	4.96	1.23	[4.89, 5.03]	34.27	2,525
Geometry or above					
Boys from high-SES families	5.84	0.94	[5.75, 5.92]	26.89	700
Girls from high-SES families	5.67	0.88	[5.58, 5.76]	27.89	726
Boys from low-SES families	5.64	1.04	[5.51, 5.77]	20.48	533
Girls from low-SES families	5.47	1.07	[5.36, 5.59]	24.74	644

Note. $N = 7{,}368$ for Algebra 1 or below and $N = 2{,}603$ for Geometry or above.
CI = confidence interval; *M* = mean; *SD* = standard deviation.

How Did Pathways From 9th to 10th Grade Math Differ among Adolescent Boys and Girls From High- and Low-SES Families?

The average progress in math levels across 9th and 10th grades among intersectional groups appears in Table 10. As noted, progress was calculated as the math level in 10th grade minus the math level in 9th grade for most students. Overall, boys from low-SES families have the lowest math progress and girls from high-SES families have the highest. Unlike expectations for success in math, we mainly find significant differences between students from high- and low-SES families and not differences by gender. Online Supporting Information: Table 4 displays these pathways in more detail.

We also examined math progress among boys and girls, high- and low-SES students, and students from non-Hispanic White and URGs to understand the role of all three facets of inequality in math progress (Table 11). On average, students from URGs and students from low-SES families had the lowest progress in math between 9th and 10th grades. However, girls progressed more than boys overall. Girls categorized as non-Hispanic White from high-SES families progressed the most overall, with an average course level increase over 1, which was higher than every other intersectional group. Boys from URGs and low-SES families progressed the least overall, with an average course level change of 0.79, which was lower than every other intersectional group except girls from URGs and low-SES families. On average, high-SES students progressed at least one-course level in math (math progress is close to 1.00), except for boys from URGs. Students from low-SES families are at risk of not progressing in math (math progress is below 0.90), except for girls the in non-Hispanic White group.

These patterns suggest that inequality in course progress operates on multiple levels. Note that although family SES differences in math progress may reflect the SES differences in students' expectations for success in

TABLE 10
Math Progress From 9th to 10th Grades by Gender and SES

Gender and SES Groups	*Mean*	*SD*	*95% CI*
Boys from high-SES families	0.96[c,d]	0.38	[0.94, 0.99]
Girls from high-SES families	1.03[c,d]	0.35	[1.00, 1.06]
Boys from low-SES families	0.85[a,b]	0.48	[0.83, 0.87]
Girls from low-SES families	0.90[a,b]	0.45	[0.88, 0.92]

Note. $N = 9{,}971$.
CI = confidence interval; *SD* = standard deviation.
[a]Significant difference with boys from high-SES families.
[b]Significant difference with girls from high-SES families.
[c]Significant difference with boys from low-SES families.
[d]Significant difference with girls from low-SES families.

TABLE 11

Math Progress From 9th to 10th Grades by Gender, SES, and Race and Ethnicity

Gender, SES, and Racial/Ethnic Groups	*M*	*SD*	*95% CI*	
Boys from high-SES families, non-Hispanic White group	0.99[b,c,e,f,h]	0.31	0.96	1.01
Boys from high-SES families, underrepresented group	0.87[a,c,d,f,g]	0.51	0.82	0.92
Girls from high-SES families, non-Hispanic White group	1.04[a,b,d,e,f,g,h]	0.32	1.01	1.07
Girls from high-SES families, underrepresented group	0.96[b,c,e,f,h]	0.35	0.91	1.00
Boys from low-SES families, non-Hispanic White group	0.89[a,c,d,f,g]	0.39	0.86	0.92
Boys from low-SES families, underrepresented group	0.79[a,b,c,d,e,g]	0.56	0.76	0.82
Girls from low-SES families, non-Hispanic White group	0.95[a,b,c,e,f,h]	0.36	0.93	0.98
Girls from low-SES families, underrepresented group	0.85[a,c,d,g]	0.54	0.82	0.88

Note. $N = 9{,}391$. Sample excludes students who did not identify as White or from an underrepresented group (Black, Hispanic/Latinx, or Native American).
CI = confidence interval; *M* = mean; *SD* = standard deviation.
[a]Significant difference with boys from high-SES families, non-Hispanic White group.
[b]Significant difference with boys from high-SES families, underrepresented group.
[c]Significant difference with girls from high-SES families, non-Hispanic White group.
[d]Significant difference with girls from high-SES families, underrepresented group.
[e]Significant difference with boys from low-SES families, non-Hispanic White group.
[f]Significant difference with boys from low-SES families, underrepresented group.
[g]Significant difference with girls from low-SES families, non-Hispanic White group.
[h]Significant difference with girls from low-SES families, underrepresented group.

math, the gender patterns did not. Girls had lower expectations than boys, but they, in fact, progressed further in math than boys. These patterns are evidence of a disconnect between expectations for success in math and math progress by gender and SES. They may reflect overconfidence among boys, and they could reflect differences in how boys and girls are treated in school—a topic we return to in our discussion of gender stereotyping in Chapter VI.

In the present chapter, we next examined how math progress differed by math position in 9th grade. As shown in Table 12, the low rates of progress for boys from low-SES families were pronounced in the on-level, but lower, math course of Algebra 1. Those boys advanced just 0.83 levels, significantly lower than every other intersectional identity group. In the more advanced math course—Geometry—boys from low-SES families still progressed at lower rates compared to boys and girls from high-SES families, but girls from low-SES families were similarly likely to progress to the next level than their male peers. Overall, these results suggest that the groups at greatest risk for being off-track are boys from low-SES families in Algebra 1, the on-level class, and girls from low-SES families in the more advanced, Geometry class.

TABLE 12
AVERAGE 10TH GRADE MATH PROGRESS BY 9TH GRADE MATH LEVEL, GENDER, AND SOCIOECONOMIC BACKGROUND

Gender and SES Groups	*Mean*	*SD*	*95% CI*	%	*N*
Algebra 1 or below					
Boys from high-SES families	$0.93^{b,c}$	0.38	[0.90, 0.96]	15.58	1,148
Girls from high-SES families	$1.00^{a,c,d}$	0.33	[0.97, 1.03]	15.04	1,108
Boys from low-SES families	$0.83^{a,b,d}$	0.48	[0.80, 0.85]	35.11	2,587
Girls from low-SES families	$0.90^{b,c}$	0.43	[0.88, 0.92]	34.27	2,525
Geometry or above					
Boys from high-SES families	$1.03^{c,d}$	0.39	[0.99, 1.07]	26.89	700
Girls from high-SES families	1.08^{d}	0.38	[1.03, 1.13]	27.89	726
Boys from low-SES families	$0.94^{a,b}$	0.47	[0.89, 0.98]	20.48	533
Girls from low-SES families	$0.91^{a,b}$	0.48	[0.87, 0.95]	24.74	644

Note. $N = 7{,}368$ for adolescents who enrolled in Algebra 1 or below in 9th grade and $N = 2{,}603$ for adolescents who enrolled in Geometry or above in 9th grade.
CI = confidence interval.
[a]Significant difference with boys from high-SES families.
[b]Significant difference with girls from high-SES families.
[c]Significant difference with boys from low-SES families.
[d]Significant difference with girls from low-SES families.

Translating Expectations into Math Progress

Did Expectations for Success in Math Predict Math Progress in 10th Grade?

Here and throughout, we present the effect of moving from low expectations for success in math (−1 *SD*) to high expectations (+1 *SD*) on the outcome of math progress, to match the conventional way of visualizing results for linear interactions (Aiken, 1991). We call this the "average treatment effect" (or ATE) when referring to the population or the "conditional average treatment effect" (or CATE) when referring to a specific group. Of course, expectations for success in math is a measured variable, not a manipulated variable, and so there is no "treatment" in this case, that is, moving from low to high expectations refers to an increase in level of the measured variable, not to an increase in an individual's expectations. We use the ATE and CATE language to follow convention from econometrics and causal inference, because our results reflect the Bayesian Causal Forest (BCF) model's best estimate for the "effect" of expectations, under the assumption that the propensity score adjustment accounts for all potential confounders. Notably, none of our conclusions depend on this strict assumption.

The BCF algorithm found that adolescents' expectations for success in math at the transition to high school were meaningfully related to their math progress overall, average treatment effect (ATE) = 0.10 [0.09, 0.11], pr(ATE > 0) = 0.99, as expected. This coefficient means that a 2 *SD* difference (i.e., from 1 *SD* below the mean to 1 *SD* above the mean) in expectations for success in math is associated with 0.10 math course levels of progress. To make this concrete, this is equivalent to going from an 84% chance of progressing from Algebra 1 to Geometry at 1 *SD* below the mean of expectations, to a 94% chance at 1 *SD* above the mean. Thus, this first model confirmed an assumption of this study, which was that expectations for success in math would predict math progress, when controlling for many potential confounding factors in the conservative model with the propensity score adjustment.

Did Expectations for Success in Math Predict Math Progress Differentially Across Gender and SES Groups?

Results across intersectional identity groups appear in Table 13 and Figure 7. These show that among youth with low expectations for success in math (−1 *SD*; 4.08 on a 7-point scale, *neither well nor poorly*), there were striking inequalities in math progress. Girls from high-SES families made the most progress (0.94 math levels in a year) and boys from low-SES families made the least (0.76 math levels in a year) (see Figure 7a). This inequality was much smaller (1.00 vs. 0.90, or 56% of the inequality in math progress among adolescents with low expectations) among youth with high expectations for success in math (+1 *SD*, 5.21 on a 7-point scale, slightly above "somewhat well"), because expectations for success in math predicted math progress more strongly for boys from low-SES families. The boxplot in Figure 7b shows the posterior distribution of the conditional average treatment effects (CATEs), which, as noted, is another way of portraying the magnitude of a regression coefficient for expectations and the uncertainty around it, separately for the four gender by SES intersectional groups.

Boys from low-SES families had the largest expectations effect, which can be seen by noting that the box does not overlap with the box for any other group (Figure 7b) and when noting that the posterior of the difference in CATEs for all groups (vs. low-SES boys) is lower than zero (Figure 7c). Thus, all groups had meaningfully weaker expectations effects than boys from low-SES families. Overall, the identity group of the adolescents who had the strongest relationship between expectations for success in math and math progress was also the most disadvantaged in math progress from 9th to 10th grade.

Did the Main Patterns Differ by 9th-Grade Math Course Level?

About 74% of the sample started in Algebra 1 or below, but this value was confounded with parental education; on average, only about 20% of adolescents from low-SES families took Geometry in 9th grade compared with about 40% of those from high-SES families.

The findings in the subsample of adolescents who started high school in Algebra 1 or below ($n = 7{,}368$) were consistent with the full sample (see Figure 8). We next examined the expectations effects among adolescents in Geometry or above in 9th grade ($n = 2{,}603$). In this more advanced course, we saw similar results, which can be seen in the BCF results showing essentially the same CATEs for expectations for success in math among Algebra I students and Geometry students (see Figure 8b,c).

TABLE 13

PREDICTED VALUES AND EXPECTATIONS EFFECTS FROM BAYESIAN CAUSAL FOREST REGRESSIONS PREDICTING MATH PROGRESS FROM 9TH TO 10TH GRADES

Statistic	Boys from Low-SES Families	Girls from Low-SES Families	Boys from High-SES Families	Girls from High-SES Families
Predicted value (high expectations, +1 *SD*)	0.90	0.93	0.99	1.00
Predicted value (low expectations, −1 *SD*)	0.76	0.83	0.90	0.95
CATE [10th, 90th %ile]	0.14 [0.12, 0.15]	0.10 [0.08, 0.11]	0.09 [0.07, 0.11]	0.06 [0.04, 0.08]
Difference in CATEs (vs. girls from high-SES families)	0.08 [0.05, 0.10]	0.04 [0.02, 0.06]	0.03 [0.01, 0.05]	—
Difference in CATEs (vs. boys from high-SES families)	0.04 [0.02, 0.07]	0.00 [−0.02, 0.03]	—	
Difference in CATEs (vs. girls from low-SES families)	0.04 [0.02, 0.06]	—		

Note. $N = 9{,}971$. The outcome variable of math progress was winsorized to range from −1 to 2. Predicted value = the expected value of the outcome, math progress, among individuals in a given intersectional identity group, estimated at high versus low levels of expectations for success in math. Expectations range from 1 = *very poorly* to 7 = *extremely well*; $-1\ SD = 4.08$ on a 7-point scale; $+1\ SD = 5.21$ on a 7-point scale. CATE = conditional average treatment effect, which is the average of the posterior distribution for the effect of moving expectations from −1 *SD* to +1 *SD*. Numbers and brackets correspond to the 10th and 90th percentiles for the posterior distributions of the CATEs. Differences in CATEs estimate the differences in posterior distributions for subgroups' CATEs, which is similar to an interaction effect (or a difference in coefficients) in a conventional regression.

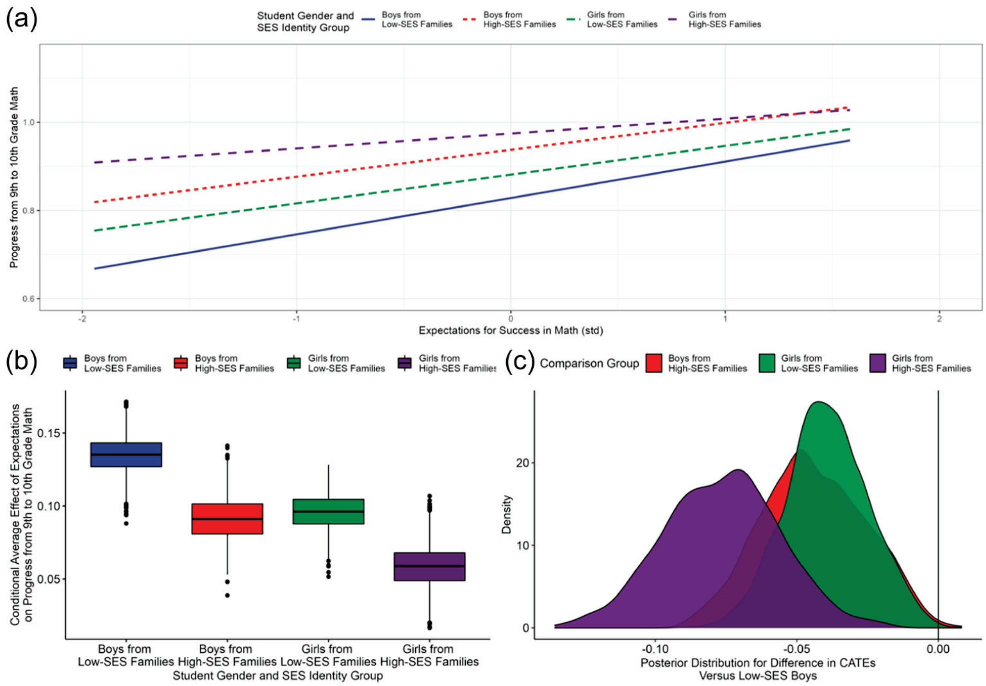

FIGURE 7.—How the link between expectations for success in math and math progress from 9th to 10th grade varied across gender and socioeconomic identity groups. $N = 9{,}971$ students. All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. (a) The predicted value of math progress from 9th to 10th grade separately by intersectional gender and SES identity groups, and by level of expectations for success in math. (b) The conditional average treatment effect (CATE) of expectations on math progress, separately for each identity group; each CATE is scaled to be equivalent to moving from -1 *SD* to $+1$ *SD* in (a). For each boxplot, the boxes depict the interquartile ranges of the posterior distributions, the lines depict the medians, and the whiskers depict the 95% intervals. (c) The posterior distributions of the differences in CATES, for each group relative to boys from low-SES families; that is, it represents the differences between the boys from low-SES families' boxplot (the blue box in (b)) and all other boxes in (b).

Did the Main Patterns Differ by Race or Ethnicity?

Descriptively, we found that SES-based inequalities in math progress among low-expectations youth were greater for students characterized as URG relative to students characterized as non-Hispanic White (Figure 9a). Boys characterized as URG from low-SES families with low expectations for success in math (-1 *SD*) were far less likely to make progress in math from 9th to 10th grade relative to girls characterized as non-Hispanic White from high-SES families with high expectations (0.70 vs. 1.02). As a result, by a wide margin, the CATE for expectations for success in math was the largest for boys characterized as URG and low-SES families (CATE = 0.15 [0.13, 0.17], pr(CATE > 0) = 0.99), as shown in Figure 9b,c. The difference in CATEs for expectations for success in math

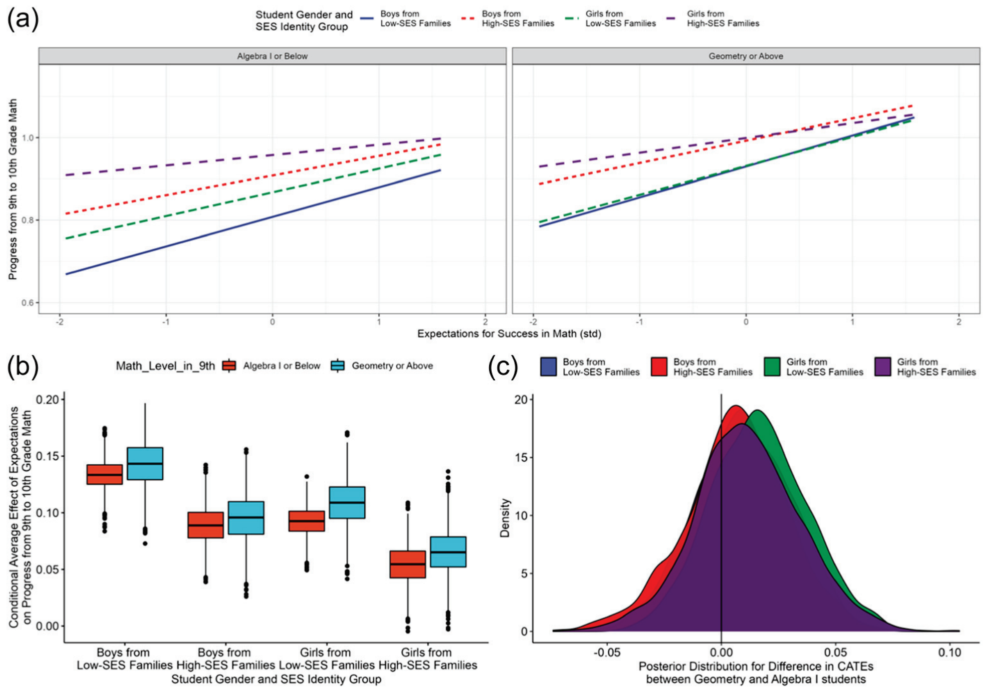

FIGURE 8.—How the link between expectations for success in math and math progress from 9th to 10th grade varied across gender and socioeconomic identity groups, separately among those who started in Algebra 1 or below in 9th grade versus those who started in Geometry or above in 9th grade. $n = 7{,}368$ for Algebra 1 or below; $n = 2{,}603$ for Geometry or above. All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. (a) The predicted value of math progress from 9th to 10th grade separately by intersectional gender and SES identity groups and 9th-grade math level, and by level of expectations for success in math. (b) The conditional average treatment effect (CATE) of expectations on math progress, separately for each identity group and 9th-grade math level; each CATE is scaled to be equivalent to moving from -1 *SD* to $+1$ *SD* in (a). For each boxplot, the boxes depict the interquartile ranges of the posterior distributions, the lines depict the medians, and the whiskers depict the 95% intervals. (c) shows the posterior distributions of the differences in CATES between the students starting in Algebra I or below versus starting in Geometry or above.

between students characterized as URG and students characterized as non-Hispanic White was meaningful for students from low-SES families (all probabilities of a difference in CATEs > 0.90), and not for students from high-SES families (all probabilities of a difference in CATEs < 0.87; see Figure 9c).

In summary, we found that the overall sample patterns held for students categorized as URG and students categorized as non-Hispanic White, in that boys from low-SES families were the lowest-performing group and showed the largest expectations effect. The magnitudes of these gendered patterns of socioeconomic disparities, however, were greater among students characterized as URG.

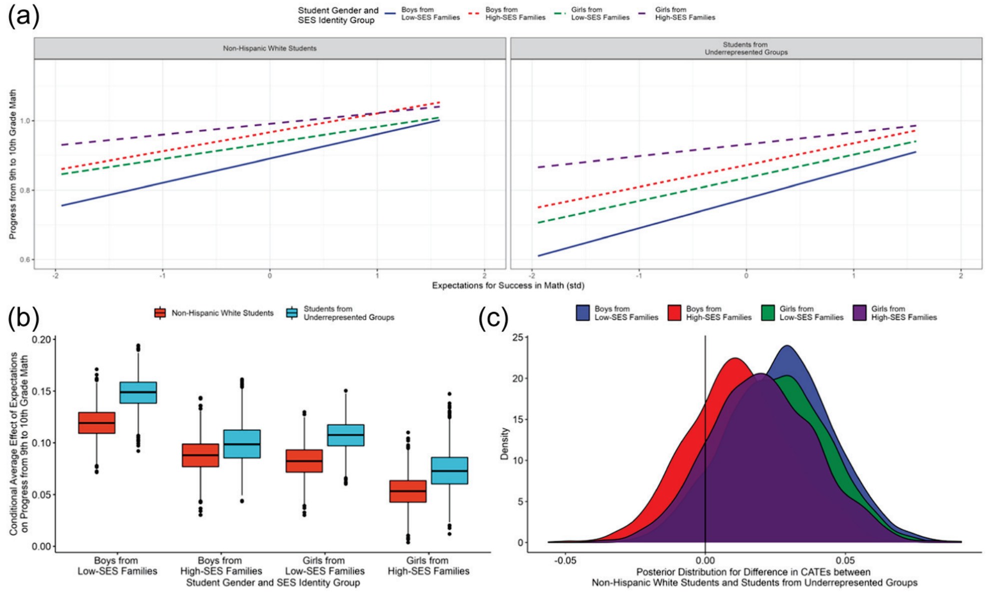

FIGURE 9.—How the link between expectations for success in math and math progress from 9th to 10th grade varied across gender and socioeconomic identity groups, separately for students from underrepresented racial/ethnic groups and White students. $N = 9{,}391$. Sample excludes students who did not identify as non-Hispanic White or from an underrepresented group (Black, Hispanic/Latinx, or Native American). All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. (a) The predicted value of math progress from 9th to 10th grade separately by intersectional gender and SES identity groups and racial and ethnic group status, and by level of expectations for success in math. (b) The conditional average treatment effect (CATE) of expectations on math progress, separately for each identity group and racial and ethnic group status; each CATE is scaled to be equivalent to moving from −1 *SD* to +1 *SD* in (a). For each boxplot, the boxes depict the interquartile ranges of the posterior distributions, the lines depict the medians, and the whiskers depict the 95% intervals. (c) The posterior distributions of the differences in CATES for students from underrepresented groups versus White students, separately by intersectional gender and SES identity groups.

Chapter IV Discussion

This chapter showed that adolescents' expectations for success in math early in high school predicted their math progress, but the strength of the association differed by family SES, gender, and racial and ethnic identity. Adolescent boys from low-SES families displayed the strongest association between expectations for success in math and math progress. Potentially, this could be because boys in that group with low expectations, on average, had few school resources, formal or informal, that helped them if they did not already believe in themselves. Adolescent girls from high-SES families were the most advantaged in this transition because their math progress appeared to be less dependent on their expectations for success in math. One explanation for this pattern is that the schools' resources supported their math achievement, even if they had low expectations. We did not find meaningful differences in expectations effects among students who began high school in a more advantaged curricular position (e.g., in Geometry or above). Overall, these findings were consistent with the Mindset × Context Theory claim that mindsets tend to predict students' outcomes more strongly among groups who face disadvantages compared to other groups.

With an understanding of the groups that are least and most at risk of not progressing in math, and those for whom expectations most strongly predicted outcomes, we next explored differences in these patterns across school contexts. If, for example, the poor performance of low-expectations boys from low-SES families were due to a general lack of school resources to support that group, then in schools that *do* provide a great deal of resources this group should show a weaker relationship between math expectations and progress. We asked: What resources at the school and classroom level may support adolescents' math progress regardless of their expectations? Does the association between expectations and math progress depend on these contextual resources? We take up these questions in the next two chapters.

V. School Context Factors That Moderate the Relation Between Expectations for Success in Math and Math Progress

Chapter IV showed that adolescents' expectations for success in math played a role in their 10th-grade math progress, but expectations mattered the most for boys from low-SES families. Specifically, boys from low-SES families with low expectations were the least likely to progress into a higher-level math course in 10th grade compared to their peers, but boys from low-SES families with *high* expectations progressed at a rate similar to that of girls and of boys from high-SES families.

Here we built on this analysis by examining the role of school contexts in the association between adolescents' expectations for success in math and their 10th-grade math progress. Our goal was to discern whether the association between expectations and math progress differed across formal and informal resources in schools and to identify contexts where adolescents from different gender/socioeconomic backgrounds showed the strongest association between expectations for success in math and math progress.

For expectations to benefit students' academic outcomes, students presumably need to be able to act on their high expectations by trying hard in school, challenging themselves, and taking more advanced coursework. Schools across the United States have different norms for these kinds of behaviors, regardless of the prior skills and current expectations of their students. During adolescence, students are particularly sensitive to the behavior of their peers, often adjusting their own behavior to fit into the academic and social norms of high school (Albert et al., 2013; Helms et al., 2014). As Mindset × Context Theory suggests, the school norms regarding effort, motivation, challenge, and risk-taking may either dampen or strengthen the association between students' expectations for success in math and their math progress (Hecht et al., 2021). We examined two potential school moderators to ascertain the role of school informal and formal context in students' math pathways.

As in earlier work by Yeager and colleagues (2019), we define formal school resources as the school's *achievement level* (Tipton et al., 2019). These formal resources refer to the kinds of opportunities available for students within the school and may impact how students advance academically. We follow the lead of that study by testing whether the effect of expectations for success in math, and its interactions with student identities, would be less pronounced in the very high-achieving schools (the top 25% of school nationally), which have many resources for supporting student success, even low-expectations students, and more pronounced in low- to medium-achieving schools (the bottom

75% of schools nationally), which have fewer resources for supporting low-expectations students' progress.

Also following the work of Yeager and colleagues (2019), we define informal school resources as the schools' *peer challenge-seeking norms* This concept refers to the degree to which the school's students are willing to challenge themselves and view challenges as opportunities for learning, even if they struggle. The school's challenge-seeking norms can signal to students whether taking academic chances, such as trying hard math problems in class or signing up for more difficult courses, is consistent with the behavior of their peers. Our analysis here parallels that earlier work by Yeager and colleagues (2019), which found a complementarity between positive student mindsets and more supportive school peer norms.

Data and Measurement

The analytical sample for the findings reported in this chapter included 9,971 students nested within the nationally representative sample of 56 schools. The regression models examined moderation by two measures: school achievement level and school challenge-seeking norms.

Formal Resources: School Achievement Level

The school achievement level variable was developed when constructing the sampling plan for the NSLM to ensure academic diversity among the schools (Tipton et al., 2019). It was estimated as a latent variable indicated by GreatSchools.org ratings and College Board data (including mean PSAT scores, AP Mathematics, and English participation), as well as state 8th-grade proficiency levels from National Assessment of Educational Progress (NAEP). Combining these data sources, the school sampling statisticians used a structural equation model to estimate a latent school achievement variable. Based on this variable and the associated loadings, a school achievement value was estimated for each school and then standardized nationally across the approximately 12,000 regular U.S. public high schools. The resulting nationally z-scored variable was then used in the sampling frame to select schools. School achievement was divided into three strata based on the 25th and 75th percentiles, corresponding to categories of low-, medium-, and high-achieving schools. We fit the BCF model using the full, continuous measure of achievement, which was allowed to have a nonlinear moderating effect. When summarizing the posterior distribution, we followed the preregistration by Yeager and colleagues (2019) in comparing higher-achieving schools (the top 25%) to all other schools (the bottom 75%).

Informal Resources: School Peer Challenge-Seeking Norms

School peer challenge-seeking norms were measured with the "Make a Worksheet" task implemented in the student survey (see Rege et al., 2020 for validation). Students were asked to create a math worksheet they would like to work on based on their current math course. They were given sets of problems from four math chapters and were asked to choose at least two from each chapter. The problems on the worksheet were labeled, "Not very challenging and you probably won't learn a lot;" "Somewhat challenging and you might learn a medium amount;" and "Very challenging but you might learn a lot." Students were told not to work on the problems when selecting them, but that they would have the opportunity to complete them if there was time. As in the analysis by Yeager and colleagues (2019), we calculated for each school the average number of hard problems the students selected, which corresponded to selecting the "very challenging but you might learn a lot" option on the worksheet. We fit the BCF model using the full, continuous measure of norms, which was allowed to have a nonlinear moderating effect. When summarizing the posterior distribution, we used the cut-point in norms from Yeager and colleagues (2019) to summarize the results (at the median, or 2.95 hard problems out of 8).

Categories of Schools Based on School Formal and Informal Resources

Using these two aspects of peer context, we placed the 56 schools into four categories: low/medium-achieving/low challenge-seeking (27 schools; low formal and informal resources), low/medium-achieving/high challenge-seeking (12 schools; low formal, high informal resources), high-achieving/low challenge-seeking (six schools; high formal, low informal resources), and high-achieving/high challenge-seeking (11 schools; high formal and informal resources).

Table 14 describes the four school contexts and their characteristics related to school quality and challenge-seeking norms. Overall, the patterns of these descriptive statistics matched expectations and pointed to the validity of the categorization scheme. As expected, the four groups of schools differed in terms of characteristics that suggest different levels of formal and informal resources to support students' expectations. Table 14 also shows school characteristics related to SES and the proportion of Black and Hispanic/Latinx students across the four peer contexts. Students in lower-achieving/low challenge-seeking schools had, on average, mothers who had attained an associate degree, while students in lower-achieving/high challenge-seeking schools had, on average, mothers who were slightly more educated but had not received a bachelor's degree. In higher-achieving schools, students' mothers, on average, had completed at least a bachelor's degree. Further, low/medium-achieving/low challenge-seeking schools had the highest rates of students receiving free and reduced-price lunch (43%) and of students from

TABLE 14

Descriptive Statistics for the Four Kinds of School Contexts

Variable	Low Formal, Low Informal: Low/Med Achievement, Low Norms			Low Formal, High Informal: Low/Med Achievement, High Norms			High Formal, Low Informal: High Achievement, Low Norms			High Formal, High Informal: High Achievement, Low Norms		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
Peer context												
School achievement level	27	−0.142	0.612	12	−0.103[c]	0.274	6	1.057[a]	0.222	11	1.160[a,b]	0.404
Challenge-seeking norms	27	2.624	0.283	12	3.287[a,c]	0.158	6	2.848	0.142	11	3.219[a,c]	0.217
Socioeconomic status												
Mother's education	27	3.296	0.473	12	3.624	0.713	6	4.104[a]	0.304	11	4.304[a,b]	0.41
Proportion free & reduced lunch	27	0.431	0.233	12	0.352	0.194	6	0.282	0.172	11	0.2[a]	0.125
Percent poverty	27	19.52	8.114	11	18.08	10.01	6	14.98	9.243	11	13.98	9.376
Percent of Black/Hispanic students	27	38.48	29.21	12	38.08	23.26	6	24.67	17.93	11	26.91	17.14
School physical structure characteristics												
Total enrollment	27	855.5[d]	612.8	12	847.8[d]	550.4	6	979.5[d]	722	11	1,847	710.2
Student–teacher ratio	27	16.81	3.833	12	17.42	4.231	6	17	3.033	11	17.36	2.203
Course information												
Proportion of schools offering AP courses	27	0.778	0.424	12	0.750	0.452	6	0.500	0.548	11	1	0

(*Continued*)

TABLE 14. (*Continued*)

Variable	Low Formal, Low Informal: Low/Med Achievement, Low Norms			Low Formal, High Informal: Low/Med Achievement, High Norms			High Formal, Low Informal: High Achievement, Low Norms			High Formal, High Informal: High Achievement, Low Norms		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
Proportion of schools offering math AP courses	27	0.407	0.501	12	0.583	0.515	6	0.500	0.548	11	0.727	0.467
Average 9th-grade math course	27	1.239	0.220	12	1.313	0.197	6	1.208	0.185	11	1.336	0.168
Proportion of students in geometry or higher	27	0.250	0.132	12	0.313	0.172	6	0.243	0.127	11	0.310	0.147
Average 10th-grade math course	27	2.133	0.260	12	2.269	0.273	6	2.196	0.244	11	2.319	0.180

Note. We include the percent of Black/Hispanic students here instead of the percent of students from underrepresented groups (Black, Hispanic/Latinx, and Native American students) because the sampling frame for the NSLM was based only on these racial/ethnic groups. See Supplemental Information for more details. Low/Med Achievement = Schools from the 0th to the 75th percentile nationally for school achievement; High Achievement = Schools above the 75th percentile. Low Norms = Schools below the national median for selection of challenging problems on the worksheet task; High Norms = Schools above the national median. The average 9th grade math ranges from 1 = below algebra to 7 = calculus.
[a]Significant difference with low/med achievement, low norms.
[b]Significant difference with low/med achievement, high norms.
[c]Significant difference with high achievement, low norms.
[d]Significant difference with high achievement, high norms.

families in poverty (19%). In higher-achieving/high challenging-seeking school, on average, 20% of the students received free or reduced-price lunch and 14% were living below the poverty level. Low/medium-achieving/schools had a similar proportion of students from URG regardless of their peer norms, as did both types of higher-achieving schools.

Overall, schools' achievement levels were related to socioeconomic measures, but challenge-seeking norms did not have a clear relationship to the socioeconomic characteristics we examined. In addition, a school's formal resources (e.g., achievement level) were related to racial/ethnic composition, but the informal resources (e.g., norms) were not. These results suggest structural differences in access to schools with higher-achieving peers, while access to schools with more learning-and-challenge-oriented peers may be more equitable.

Turning our attention to course characteristics, we saw that, on average, students across the four school types were similar in their math course-taking in 9th and 10th grade. Across all peer contexts, on average, students tended to be in a class slightly above Algebra in 9th grade, and they tended to be in Geometry in the 10th grade. Yet when considering the proportion of students in Geometry or higher in 9th grade, we saw that the high challenge-seeking contexts enrolled about 30% of students in Geometry or above compared to the low challenge-seeking contexts, which had about 25% of their students in Geometry or higher. Within each context, the proportion of schools offering an AP course was similar. But all higher-achieving/high challenge-seeking schools offered an AP math course, while only about half the schools in each of the other peer contexts did so. Thus, the four school contexts we examined presented students with different types of peers and opportunities to take math courses. In particular, higher-achieving/high challenge-seeking schools provided many opportunities that might help even low-expectations students to make progress in math (which could attenuate expectations effects).

Table 15 presents descriptive statistics that reveal the characteristics of the students in the four kinds of peer contexts. As expected, high-achieving schools had more students from high-SES families, and low/medium-achieving schools had more students from low-SES families. Still, within each kind of school there was enough variability in student SES to test the present hypotheses.

Results

Did Expectations for Success in Math and Math Progress Differ by School Context?

As a preliminary matter, we asked how students' expectations for success in math and math progress differed by school context. We considered the means and standard deviations of expectations for success in math and 10th-grade math progress by students' gender and SES in each kind of school context. As Table 16 shows, boys and girls from high-SES families and boys from low-SES families were similar in their expectations for success in math

TABLE 15

Distribution of Adolescent Gender and SES Groups by Peer Context

Gender and SES Groups	School/Peer Contexts								All	
	Low Formal, Low Informal: Low/Med Achievement, Low Norms		Low Formal, High Informal: Low/Med Achievement, High Norms		High Formal, Low Informal: High Achievement, Low Norms		High Formal, High Informal: High Achievement, High Norms			
	%	*N*	%	*N*	%	*N*	%	*N*	%	*N*
Boys from high-SES families	12.67%	496	16.16%	274	21.71%	226	25.68%	852	18.53%	1,848
Girls from high-SES families	12.16%	476	14.5%	246	23.05%	240	26.28%	872	18.39%	1,834
Boys from low-SES families	36.41%	1,426	36.08%	612	26.8%	279	24.2%	803	31.29%	3,120
Girls from low-SES families	38.76%	1,518	33.25%	564	28.43%	296	23.84%	791	31.78%	3,169
Total	100%	3,916	100%	1,696	100%	1,041	100%	3,318	100%	9,971

Note. Low/Med Achievement = Schools from the 0th to the 75th percentile nationally for school achievement; High Achievement = Schools above the 75th percentile. Low Norms = Schools below the national median for selection of challenging problems on the worksheet task; High Norms = Schools above the national median.

TABLE 16

Means and Standard Deviations of Expectations and Math Progression by School Type

Gender and SES Groups	Dependent Measure: Expectations of Success				Dependent Measure: Math Progression			
	Low/Med Achievement Low Norms	Low/Med Achievement High Norms	High Achievement Low Norms	High Achievement High Norms	Low/Med Achievement Low Norms	Low/Med Achievement High Norms	High Achievement Low Norms	High Achievement High Norms
Overall mean	5.12 (1.18)	5.18 (1.19)	$5.32^{a,b}$ (1.01)	$5.30^{a,b}$ (1.08)	0.85 (0.46)	$0.89^{a,c}$ (0.42)	0.98^{a} (0.31)	$0.92^{a,b,c}$ (0.34)
Boys from high-SES families	5.42 (1.09)	5.48 (1.06)	5.46 (1.03)	5.48 (1.05)	0.91 (0.43)	0.96 (0.38)	0.98^{a} (0.25)	0.95 (0.29)
Girls from high-SES families	5.24 (1.11)	5.41 (1.12)	5.39 (0.90)	5.37 (1.02)	0.95 (0.36)	0.99 (0.22)	1.04^{a} (0.28)	1.00^{a} (0.25)
Boys from low-SES families	5.12 (1.20)	5.12 (1.19)	5.27 (0.99)	5.18 (1.17)	0.77 (0.49)	0.83^{a} (0.46)	0.91^{a} (0.35)	0.85^{a} (0.42)
Girls from low-SES families	4.99 (1.18)	5.01 (1.24)	5.19^{a} (1.07)	5.17^{a} (1.04)	0.87 (0.46)	0.87^{c} (0.45)	1.00^{a} (0.33)	0.89^{c} (0.35)

Note. All differences are within the same intersectional identity group. Low/Med Achievement = Schools from the 0th to the 75th percentile nationally for school achievement; High Achievement = Schools above the 75th percentile. Low Norms = Schools below the national median for selection of challenging problems on the worksheet task; High Norms = Schools above the national median. Letters correspond to significance tests across columns within rows.

[a]Significant difference with low/med achievement, low norms.
[b]Significant difference with low/med achievement, high norms.
[c]Significant difference with high achievement, low norms.
[d]Significant difference with high achievement, high norms.

across the four different peer contexts. An intersectional difference emerged, however. In low/medium-achieving and low challenging-seeking schools—that is, schools with the poorest outcomes overall—girls from low-SES families had significantly lower expectations for success in math than they did in high-achieving, more supportive contexts.

Turning to the focal math progress variable, adolescents from low/medium-achieving- low challenge-seeking schools generally tended to progress less compared to their peers in other contexts. This finding is not surprising because these schools have the fewest formal and informal resources. Next, math progress differed by gender and SES identity groups across school types, as shown in Table 16. In general, students made the most progress in math, and showed relatively small intersectional disparities, in high-achieving schools.

The group with the lowest rate of math progress in this sample was boys from low-SES families in the least supportive schools, which were schools that were low/medium-achieving (the bottom 75%) with low challenge-seeking norms (see column 5 of Table 16). In those schools, the disparities between boys from low-SES families and students from high-SES families of either gender were strikingly large. Higher challenge-seeking norms, however, were associated with greater math progress overall and also reduced disparities between boys from low-SES families and their higher-SES peers (column 6 of Table 16). Interestingly, math progress for girls from low-SES families was not greater when challenge-seeking peer norms were greater (see Table 16). Overall, boys from low-SES families in low/medium-achieving schools had the greatest risk for inadequate progress in math. Positive peer norms, however, seemed to support that group of boys.

How Does the Association Between Expectations for Success in Math and Math Progress Differ Across Student Intersectional Identity Groups and School Contexts?

The same multilevel BCF model fit that was summarized in Chapter IV also included the context-level moderators described here in Chapter V (also see the 2019 analysis by Yeager and colleagues of school achievement level in this dataset). Expected values of math progress, by expectations level, intersectional identity group, and school type are presented in Table 17.

Considering the gendered pattern of socioeconomic differences in CATEs across schools, we found that the CATE for expectations for success in math was greatest for boys from low-SES families when they were in low/medium-achieving schools (CATE = 0.15 [0.13, 0.16], pr(CATE > 0) = 0.99), and the CATE was weakest for girls from high-SES families in schools with high challenge-seeking norms (CATE = 0.04 [0.02, 0.06], pr(CATE > 0) = 0.99). The posterior probability that the Expectations × School achievement × Challenge-seeking norms interaction was different for boys from low-SES families and girls from high-SES families was 0.98, suggesting

TABLE 17

Between-School Analyses: Results of a Bayesian Causal Forest Regression Predicting Math Progress From 9th to 10th Grade

School Type	Statistic	Boys from Low-SES Families	Girls from Low-SES Families	Boys from High-SES Families	Girls from High-SES Families
High achievement, high norms	Predicted value (high expectations)	0.91	0.93	0.99	1.01
	Predicted value (low expectations)	0.81	0.86	0.91	0.96
	CATE (effect of expectations)	0.11 [0.09, 0.13]	0.06 [0.04, 0.08]	0.08 [0.05, 0.10]	0.04 [0.02, 0.06]
High achievement, low norms	Predicted value (high expectations)	0.95	0.98	1.00	1.03
	Predicted value (low expectations)	0.83	0.88	0.90	0.95
	CATE (effect of expectations)	0.13 [0.10, 0.16]	0.10 [0.07, 0.12]	0.10 [0.08, 0.13]	0.08 [0.05, 0.11]
	Difference in CATEs (vs. high achievement, high norms schools)	0.02 [0.00, 0.05]	0.03 [0.01, 0.06]	0.03 [0.00, 0.05]	0.04 [0.01, 0.06]
Low/medium achievement, high norms	Predicted value (high expectations)	0.90	0.90	0.99	0.99
	Predicted value (low expectations)	0.75	0.80	0.90	0.95
	CATE (effect of expectations)	0.15 [0.13, 0.17]	0.10 [0.07, 0.12]	0.09 [0.07, 0.12]	0.04 [0.02, 0.07]
	Difference in CATEs (vs. high achievement, high norms schools)	0.04 [0.02, 0.07]	0.03 [0.01, 0.06]	0.02 [−0.01, 0.04]	0.00 [−0.02, 0.03]
Low/medium achievement, low norms	Predicted value (high expectations)	0.87	0.93	0.97	0.99
	Predicted value (low expectations)	0.73	0.82	0.86	0.91
	CATE (effect of expectations)	0.15 [0.13, 0.16]	0.11 [0.09, 0.13]	0.11 [0.09, 0.14]	0.09 [0.06, 0.11]
	Difference in CATEs (vs. high achievement, high norms schools)	0.04 [0.02, 0.06]	0.05 [0.03, 0.07]	0.04 [0.04, 0.06]	0.04 [0.02, 0.07]

Note. $N = 9{,}971$ students. Low/med achievement = Schools from the 0th to the 75th percentile nationally for school achievement; High achievement = Schools above the 75th percentile. Low norms = Schools below the national median for selection of challenging problems on the worksheet task; High norms = Schools above the national median. All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. Math progress variable winsorized to range from −1 to 2. Predicted value = the expected value of the outcome, math progress, among individuals in a given identity group, estimated at high versus low levels of expectations. Low expectations = −1 *SD*, or 4.08 on a 7-point scale; High expectations = +1 *SD*, or 5.21 on a 7-point scale. CATE = conditional average treatment effect, which is the average of the posterior distribution for the effect of moving expectations from −1 *SD* to +1 *SD*. Numbers and brackets correspond to the 10th and 90th percentiles for the posterior distributions of the CATEs. Differences in CATEs estimate the differences in posterior distributions for subgroups' CATEs, which is similar to an interaction effect (or a difference in coefficients) in a conventional regression analysis.

strong evidence for an intersectional difference in the moderating effects of school contexts.

Looking closer at the different groups, we found that many of the results were consistent with the compensatory hypothesis. Adolescents from the intersectional identity group with highest average math progress and in schools with the best formal and informal resources showed the weakest effects of expectations for success in math (girls from high-SES families in high achieving, high norms schools); for that group of adolescents, if they had low expectations, they still tended to make progress in math at high rates (see Table 17). Thus, the informal and formal resources in the school context appeared to compensate for low levels of the psychological resource of expectations for success in math. In fact, girls from high-SES families with *low* expectations in high-achievement, high challenge-seeking schools made more progress in math (0.96) than boys from low-SES families with *high* expectations in low/medium-achieving, low norms schools (0.87, see Table 17).

The results were also consistent with the accumulated disadvantage (or negative complementarity) hypothesis (see Table 17). This is the hypothesis that the negative effect of low expectations will be the most striking in the most unsupportive contexts. Overall, the math progress rates for students with low expectations for success in math were the weakest in low/medium achieving schools with low peer norms (0.80). As a result, the CATE for expectations was stronger in low/medium achieving schools with low peer norms than it was in high-achieving schools with strong peer norms (posterior probability that overall difference in CATEs $> 0 = 0.99$). This finding was consistent across intersectional identity groups (see Figure 10c).

We saw a few notable differences in these overall patterns across intersectional gender and SES identity groups. Only girls from high-SES families, and not any other group, showed a compensatory effect for peer norms in low/medium-achieving schools. In low/medium-achieving schools, low-expectations girls from high-SES families profited from a positive peer norm, lifting their outcomes to a level that was comparable to girls from that group in high-achieving schools. For all other intersectional identity groups, norms were compensatory (i.e., reduced the CATE for expectations) *only* in high-achieving schools (probability of a five-way interaction for differences in CATEs $= 0.65$).

Another way to describe the findings is that there was moderate evidence for an interactive effect of the school's achievement level and challenge-seeking norms on the compensatory effect for all groups except girls from high-SES families. Looking at Figure 10b, we see that the moderating effect of a school's achievement level on the magnitude of the CATE for expectations was apparent only when it was paired with higher norms (except for girls from high-SES families).

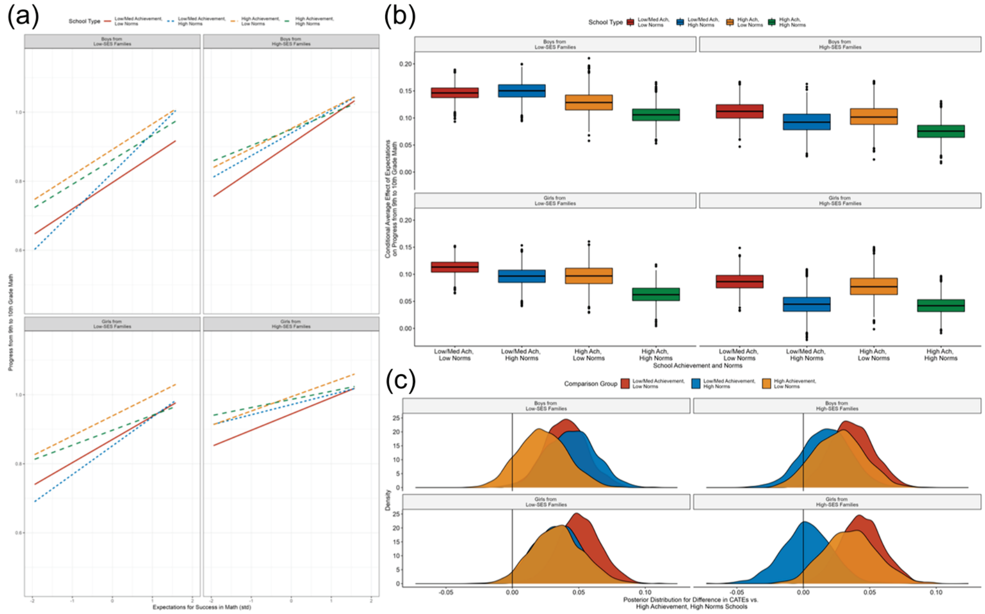

FIGURE 10.—Between-school variation in the link between expectations for success in math and math progress from 9th to 10th grade, across gender and socioeconomic identity groups, as a function of school formal and informal resources. $N = 9{,}971$ students. Low/med ach = schools from the 0th to the 75th percentile nationally for school achievement; High ach = schools above the 75th percentile. Low norms = schools below the national median for selection of challenging problems on the worksheet task; High norms = schools above the national median. All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. (a) The predicted value of math progress from 9th to 10th grade separately by intersectional gender and SES identity groups and school type, and by level of expectations for success in math. (b) The conditional average treatment effect (CATE) of expectations on math progress, separately for each intersectional identity group and school type; each CATE is scaled to be equivalent to moving from −1 *SD* to +1 *SD* in (a). For each boxplot, the boxes depict the interquartile ranges of the posterior distributions, the lines depict the medians, and the whiskers depict the 95% intervals. (c) The posterior distributions of the differences in CATES for all school types relative to the most advantaged schools—those with high achievement levels and high norms.

Chapter V Discussion

This chapter examined whether the link between expectations for success in math and math progress varied by school peer contexts, defined by school achievement level and challenge-seeking norms. Achievement level, measured via administrative records, was conceptualized as a formal resource that determines the types of academic supports that are available to students. This formal resource predicted greater math progress overall. The school's challenge-seeking norms, measured through a behavioral task, were an informal resource for students that encouraged peers to challenge themselves more.

Our conservative but flexible Bayesian model showed the following. In low/medium-achieving schools (the bottom 75% of schools nationally), the informal resource of a positive peer school norm (a) predicted greater math progress overall, (b) lifted math progress for boys from low-SES families when they had high expectations, and (c) buffered girls from high-SES families from having their low expectations derail their math progress. A school's formal and informal resources worked together for most groups: except for the highest-achieving group (girls from high-SES families); school achievement level related only to better outcomes for low-expectations students (and weaker effects of expectations) when paired with high peer norms.

These findings align with the large and growing amount of research in social neuroscience and neuroendocrinology that has pointed to adolescents' enhanced sensitivity to peer influence during the mid- to late-adolescence period studied here (Albert et al., 2013; Choukas-Bradley et al., 2014; Dahl et al., 2018; Paluck & Shepherd, 2012; Yeager et al., 2018). What they add to this literature is an assessment of how individual differences (prior expectations for success in math) and group differences (intersectional gender and SES identities) result in differential links with school peer norms.

These findings also align with some of the predictions of Mindset × Context Theory, but not all of them. Using the present mindset, expectation for success in math, in a BCF analysis designed to move closer to causal effects, we found results that mirrored some of the experimental findings from the growth mindset intervention reported in the earlier study by Yeager and colleagues (2019). The strongest link between the mindset (expectations) appeared for the group at most risk for poor outcomes (boys from low-SES families), in contexts that were not the highest-achieving (low/medium-achieving schools). This is a conceptual replication, therefore, of some of the NSLM's experimental findings.

At the same time, there were some surprises in these results that can support future theory-building. We found that the school's peer norms were moderators of the expectations effects only in the higher-achieving schools for most of the intersectional identity groups. This is not what was found for the experimental mindset intervention in the NSLM. In the NSLM randomized trial (Yeager et al., 2019), we found that a growth mindset treatment was moderated by peer norms most strongly in the low/medium achieving schools. Thus, Chapter V raises the possibility that for measured variables such as expectations for success in math there is a kind of compensatory effect of the most supportive contexts. The Mindset × Context framework will need to be adjusted to accommodate this kind of finding if it is found consistently. In Chapter VI, we went beyond these results by conducting a different test of Chapter V's "compensation" and "complementarity" findings. In the next chapter, we used a different contextual moderator: students' perceptions of their teachers' gendered math stereotyping in the classroom.

VI. The Role of Perceived Classroom Stereotyping in Math Process

The previous two chapters examined individual- and school-level predictors of adolescents' progress in math as they transitioned from 9th to 10th grade. This chapter built on the prior two by shifting the focus from the school level to the classroom. This allowed for an investigation of finer-grained processes that could influence students' daily motivation. Of particular interest was whether groups of students felt stereotyped by their teachers within their math classrooms. We wanted to know whether adolescents perceived that their teachers' and/or peers' judgments of their math ability would be influenced by their genders, and how this influence could lead to dashed expectations in math progress or not.

Classroom cultures in which students feel stereotyped could affect students' motivation to progress in math in both negative and positive ways. First, negative stereotypes about one's group (e.g., gender, racial and ethnic identity) might *undermine* a student's progress in math (see Steele, 1997). For example, a traditional stereotype in the United States is that boys are more naturally gifted at math than girls, and such stereotypical beliefs are negatively associated with math achievement for girls (Alan et al., 2018; Barth & Masters, 2020; Beilock et al., 2010; Breda et al., 2020). These negative stereotypes about girls are learned rapidly in early and middle childhood, often without any argument or direct instruction, through the subtle ways that our society structures power and influence in math and the sciences, and through the language we use to describe groups' abilities (Bigler & Liben, 2006; Cimpian & Salomon, 2014). Second, positive stereotypes about one's group have the potential to induce "stereotype lift," whereby individuals *benefit* from a positive stereotype about their group (or from downward comparisons with a negatively stereotyped outgroup; Walton & Cohen, 2003). However, positive stereotypes may also backfire, especially when combined with low expectations for success. For example, boys may be unlikely to pursue advanced courses in math if they have low expectations for success in math and, perhaps as a result, do not believe that they can live up to the positive stereotype about their group. They may assume that if they do not have strong math ability despite the perceived advantage of being a boy, they must *really* not be cut out for advanced math. Indeed, experimental research shows that linking success in a domain to any category can undermine children's persistence when they face failure (Cimpian et al., 2012). This chapter, therefore, offers a test of how students' perceptions of gender stereotyping within their classroom play out in the real world. As such, it offers a critical opportunity to either confirm or suggest revisions to laboratory-based experimentation on math stereotyping.

The first research question was whether the association between adolescents' expectations for success for math in 9th grade and math progress in 10th grade varied significantly between classrooms. Answering this question could reveal whether, in general, expectations matter in similar ways in all contexts. That is, we can test the “mindset alone” hypothesis, which is the notion that students can use their psychological resources, such as expectations for success in math, to the same extent in all settings, regardless of the local culture (see Hecht et al., 2021). If we found variability in the link between expectations for success in math and math progress across contexts, this would suggest that there may be classroom factors that hinder or enhance a student's ability to profit from high expectations.

The second research question was whether perceived classroom gender stereotyping could explain why expectations for success in math were sometimes strongly linked to math progress, and other times were not. As noted, we tested the possibility that girls' math progress was greatest when they had high expectations for success in math and when there was very little perceived stereotyping, and worst when they had low expectations for success in math and perceived a great deal of stereotyping. Further, we tested the possibility that expectations for success in math were strongly associated with math progress for boys from low-SES families when perceived classroom gender stereotyping was high. If true, this could be because these boys felt discouraged from progressing in math when they did not believe they could live up to positive stereotypes about their ability in math (see Rogers & Feller, 2016).

Methods

The procedure for the present study was similar to that in the previous two chapters, using the same outcome variable and measures in the models. We also included adolescents' perceptions of gender stereotypes in the math classroom, which was measured on the second student survey (in most schools, administered 6–10 weeks into the school year). We took this measure during the second survey because, by this point, adolescents had had sufficient time to form perceptions of gender stereotyping in their math classes.

Analytic Subsample

The subsample for these analyses consists of 6,856 adolescents nested within 229 math teachers (see Table 1 in Chapter III for more details). The sample is smaller than the sample used in the previous two chapters because we could only include students who were matched with teachers and for whom there were student ratings of perceived stereotyping. Adolescents with multiple math teachers in this semester were paired with only a single teacher on the basis of which teacher taught the highest-level math class. We assumed that adolescents' experiences in their highest-level math classes would be more relevant to their progress in math the following year than their experiences in lower-level math classes would be. Adolescents were excluded from the sample if they had multiple teachers at the same math level who had completed the survey. (If these adolescents had been included in the sample, we could not have determined in which math classroom they were perceiving gendered stereotyping.) Finally, as with the sample in the previous two chapters, adolescents were excluded from the sample if they were missing an observation for the outcome or if they took a math course higher than Geometry in 9th grade (except in schools where it was normative for students to take Algebra 2 prior to Geometry, in which case students taking Algebra 2 were retained in the sample). Analyses in Chapter III found that the subsample for these analyses did not differ meaningfully along key demographic characteristics relative to the sample included in the previous two analytic chapters.

Measurement

Again, the dependent variable was adolescents' progress in math between 9th and 10th grades. Independent variables included adolescents' expectations for success in math, gender, SES, race and ethnicity, and 8th-grade GPA. For perceived stereotyping in the classroom, adolescents responded to the question, "In math class, how much do you worry that people's judgments of you will be affected by your gender?" on a five-point Likert scale ranging from "not at all" to "an extreme amount." Unfortunately, the NSLM did not include a similar question about perceived stereotyping by SES.

Descriptive Statistics

Overall, perceptions of classroom stereotyping were low ($M = 1.62$, $SD = 1.00$). One-third of adolescents, however, reported a level of perceived stereotyping greater than zero. This is practically significant because any level of perceived stereotyping may impact students as they progress through high school math.

To examine whether perceived gender stereotyping differed by student characteristics, in a preliminary analysis we regressed perceived gender stereotyping on gender and SES in a multilevel model with a random intercept for teacher. Perceived gender stereotyping was somewhat greater among students from low-SES families ($M = 1.65$, $SD = 1.00$) than students from high-SES families ($M = 1.57$, $SD = 0.99$), although this difference was not very large ($b = -0.07$, $t = -1.77$, $p = .077$). We did not find an interaction between gender and SES on perceived stereotyping, ($b = 0.04$, $t = 0.537$, $p = .591$) and perceived gender stereotyping did not significantly differ by gender ($b = -0.02$, $t = -0.60$, $p = .547$). While this may seem surprising, gendered stereotypes about who is better at math (which preference boys) and who is better in school in general (which preference girls) are potentially both present in math classrooms (Heyder & Kessels, 2017; Riegle-Cumb & Peng, 2021).

Results

Classroom-Level Variation in the Association between Expectations for Success in Math and 10th-Grade Math Progress

For the present chapter, we fit a new BCF model that nested students within teachers. We summarized the posterior distribution of the BCF model fit to examine whether the association between expectations for success in math and 10th-grade math progress varied significantly between classrooms. We tested whether the association between expectations for success in math and 10th-grade math progress varied across *local intersectional identity groups* (i.e., clusters of demographic groups at the intersection of gender and SES within teachers' course sections (see Walton et al., in press) ($N_{\mathrm{CLUSTERS}} = 793$; $M_{\mathrm{STUDENTS/CLUSTER}} = 14.63$, $Mdn_{\mathrm{STUDENTS/CLUSTER}} = 12$; Figure 11). We provide more details in the online Supporting Information. For the reasons discussed in Chapter III, we did not test for racial or ethnic variability in the association between expectations for success in math and math progress: There was low racial/ethnic diversity within schools and within SES categories.

We found substantial variability in the association between expectations for success in math and math progress across intersectional identity groups.

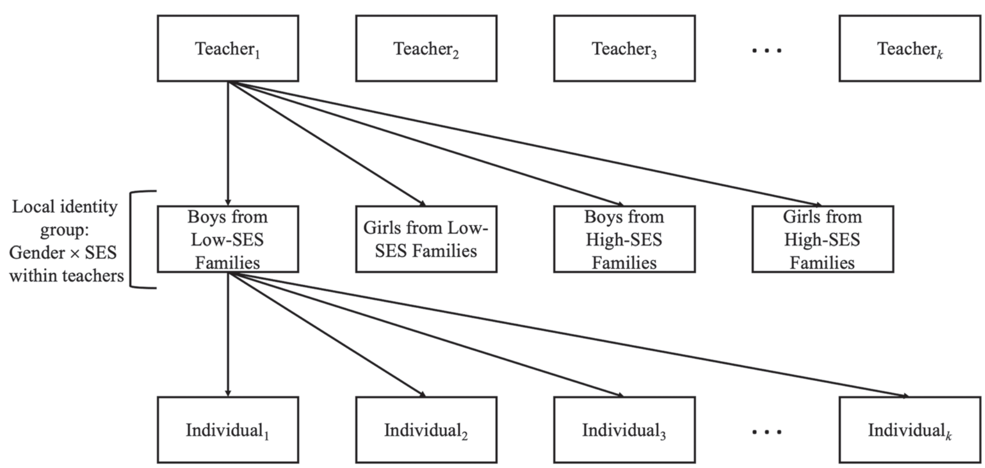

FIGURE 11.—Local intersectional identity groups: Conceptual diagram depicting the gender × SES within teacher clusters in which adolescents were nested for the Chapter VI analyses.

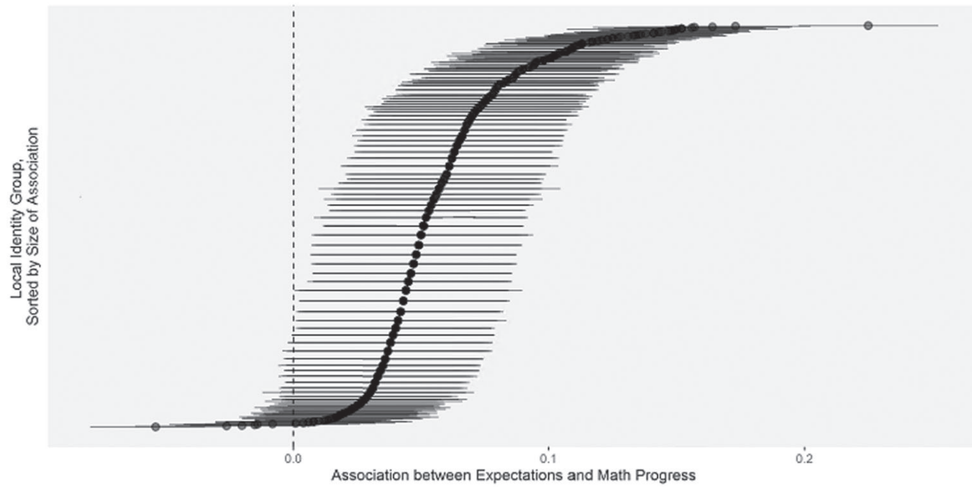

FIGURE 12.—Variation in the magnitude of association between expectations for success in math and math progress across local intersectional identity groups (SES by gender groups within teachers). Individual points represent the effect of expectations for success in math on math progress from 9th to 10th grade, for a given local identity group (SES by gender groups within teachers), estimated in a multilevel Bayesian Causal Forest model with random slopes for local identity groups. Horizontal lines represent 95% posterior density intervals.

In a null random intercept model, the standard deviation of the association across intersectional identity groups was 0.03, which was nearly half (49%) of the average association within this analytic sample (0.06). Variability in the association between expectations for success in math and math progress across intersectional identity groups, estimated in BCF, is displayed in Figure 12.

These results indicate that although adolescents' expectations for success in math were an important predictor of their math progress on average, the association between expectations and 10th-grade math progress differed meaningfully across classrooms and intersectional identity groups. From a broad perspective, these findings suggested that to understand the role of adolescents' expectations in their course-taking trajectories in math, we must also assess how these expectations interacted with their classroom contexts. In the following analyses, we examined how one predictor in particular—perceived gender stereotyping in the classroom—moderated the relation between adolescents' expectations for success in math and their subsequent progress in math. We attended to differences by adolescent gender and SES.

The Role of Perceived Gender Stereotyping Within the Math Classroom

The focal context-level moderator in this chapter was perceived classroom gender stereotyping. Because stereotyping could be perceived differently by different groups in the same classroom, we averaged the adolescent-level measure of perceived stereotyping to the intersectional identity group level (i.e., all boys from low-SES families within the same teacher's class contributed to a single mean for that intersectional identity group). Results for this variable therefore represent the role of a particular demographic group's average experience of stereotyping within a given classroom. Predicted values, CATEs for expectations, and differences in CATEs between classes with high versus low perceived stereotyping are presented in Table 18.

First, we found that classroom stereotyping was associated with lower rates of math progress for each subgroup, on average (see Figure 13a). In addition, stereotyping moderated the association between expectations for success in math and math progress. Among boys from low-SES families, girls from low-SES families, and girls from high-SES families, the association between expectations for success in math and math progress was stronger in classrooms with higher perceived gender stereotyping than classrooms with lower perceived gender stereotyping (probability of a difference in CATEs between classes with high vs. low perceived stereotyping >0.94 for each of these three subgroups; see Figure 13b,c). This pattern suggests that high expectations for success in math helped to buffer these groups of students against the negative effects of perceived gender stereotyping (see Figure 13a). Interestingly, this pattern of moderation did not emerge for boys from high-SES families (probability of a difference in CATEs between classes with high vs. low perceived stereotyping = 0.62). That is, perceived stereotyping did not seem to negatively affect math progress more among boys from high-SES families with low expectations than those with high expectations. This finding may reflect that boys from high-SES families are not typically subjected to negative stereotypes about their math ability.

Another way to understand the role of perceived stereotyping is to examine how this classroom factor contributed to math progress as compared to structural markers of disadvantage (e.g., socioeconomic status). For example, when girls from high-SES families (i.e., the group with the highest rates of math progress overall) had low expectations for success in math and experienced classrooms with high levels of perceived gender stereotyping, they showed rates of math progress (0.82 math levels) that were as low as those of boys from low-SES families (i.e., the group with the lowest rates of math progress overall) with low expectations for success in classrooms with low levels of perceived gender stereotyping (0.80 math levels). Thus, girls from high-SES were meaningfully held back by low expectations for success in math if they encountered a classroom in which they perceived a high degree of stereotyping, despite other perceived advantages in school overall (as shown in Chapter IV). That is, even among the demographic group with the highest base rate of math progress, experiencing gender stereotyping while holding low expectations for success substantially reduced the likelihood of making progress in math from 9th to 10th grade.

TABLE 18

Between-Teacher Analyses: Results of a Mixed Effects Regression Predicting Math Progress From 9th to 10th Grade

Classroom Type	Statistic	Boys from Low-SES Families	Girls from Low-SES Families	Boys from High-SES Families	Girls from High-SES Families
Low stereotyping	Predicted value (high expectations)	0.93	0.97	0.99	1.01
	Predicted value (low expectations)	0.80	0.86	0.89	0.93
	CATE (effect of expectations)	0.14 [0.12, 0.15]	0.10 [0.09, 0.12]	0.10 [0.08, 0.13]	0.08 [0.06, 0.10]
High stereotyping	Predicted value (high expectations)	0.84	0.9	0.9	0.96
	Predicted value (low expectations)	0.66	0.75	0.79	0.82
	CATE (effect of expectations)	0.18 [0.15, 0.22]	0.15 [0.11, 0.19]	0.11 [0.06, 0.16]	0.14 [0.11, 0.19]
	Difference in CATEs (high vs. low stereotyping)	0.05 [0.02, 0.08]	0.05 [0.01, 0.08]	0.01 [−0.04, 0.06]	0.06 [0.01, 0.10]

Note. $N = 6{,}856$ students nested within 731 local identity groups. Perceived classroom stereotyping was measured as the average perceived gender stereotyping within a local intersectional identity group (i.e., Gender × SES group within a classroom). All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within schools. Math progress variable winsorized to range from −1 to 2. Predicted value = the expected value of the outcome, math progress, among individuals in a given identity group, estimated at high versus low levels of expectations for success in math. Low expectations = −1 *SD*, or 4.08 on a 7-point scale; High expectations = +1 *SD*, or 5.21 on a 7-point scale. CATE = conditional average treatment effect, which is the average of the posterior distribution for the effect of moving expectations from −1 *SD* to +1 *SD*. Numbers and brackets correspond to the 10th and 90th percentiles for the posterior distributions of the CATEs. Differences in CATEs estimate the differences in posterior distributions for subgroups' CATEs, which is similar to an interaction effect (or a difference in coefficients) in a conventional regression analysis.

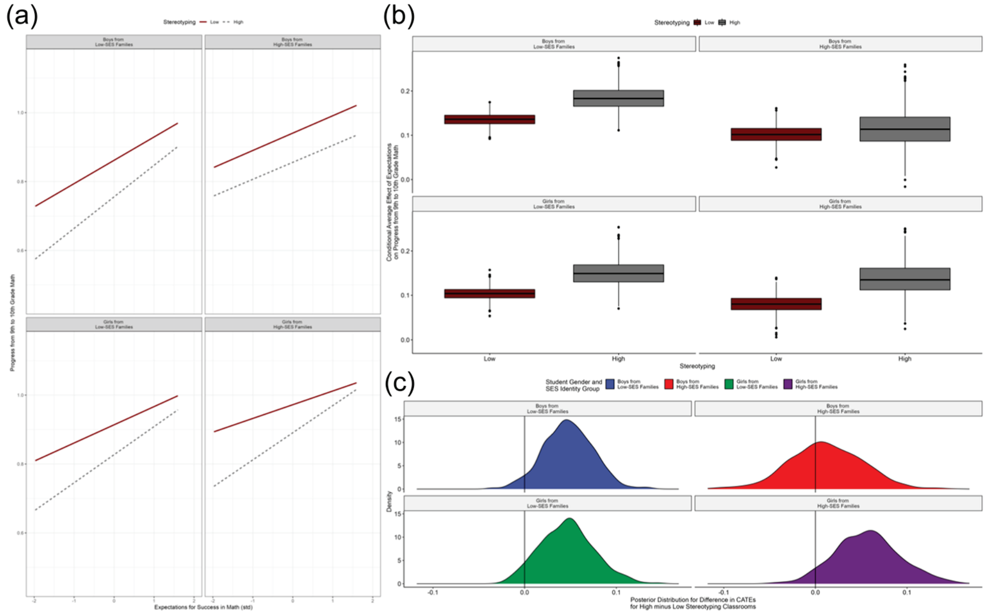

Figure 13.—Between-teacher variation in the link between expectations for success in math and math progress from 9th to 10th grade, across gender and socioeconomic identity groups, as a function of classroom gender stereotyping. $N = 6{,}856$ students. Low stereotyping = schools at or below the 75th percentile for perceived classroom stereotyping, as defined by the average of students' ratings of teachers, separately for each local intersectional identity group; High stereotyping = schools above the 75th percentile. All results depicted come from a multilevel Bayesian Causal Forest model fit, with students nested within local intersectional identity groups. (a) The predicted value of math progress from 9th to 10th grade separately by intersectional gender and SES identity groups and perceived classroom stereotyping level, and by level of expectations for success in math. (b) The conditional average treatment effect (CATE) of expectations on math progress, separately for each identity intersectional group and level of perceived classroom stereotyping; each CATE is scaled to be equivalent to moving from −1 *SD* to +1 *SD* in (a). For each boxplot, the boxes depict the interquartile ranges of the posterior distributions, the lines depict the medians, and the whiskers depict the 95% intervals. (c) The posterior distributions of the differences in CATES for high versus low perceived classroom stereotyping, separately for the four intersectional identity groups.

Chapter VI Discussion

The analyses reported in this chapter built on the findings of previous chapters in two important ways. First, the analyses indicated that the association between adolescents' expectations for success in math and math progress is related to adolescents' *perceptions of classroom gender stereotyping*. Although adolescents' expectations for success in math were, on average, an important predictor of their subsequent course-taking, the role of expectations differed between classrooms. In some classrooms, expectations may be less important; for example, when the classroom culture supports all adolescents' progression in math, buffering adolescents against possible negative effects of low expectations for success in math. In other classrooms, expectations may be very important, leading more confident adolescents to progress to higher levels of math, but discouraging less confident adolescents from doing so.

Second, these analyses investigated *perceived gender stereotyping*, a classroom-level factor that moderated the association between adolescents' expectations for success in math and their math progress. These findings revealed a different pattern of moderation across intersectional identity groups relative to school-level effects. Girls from high-SES families, for example, showed dramatically reduced rates of math progress if they had low expectations for success in math and perceived that they were in a classroom where they felt their math ability was judged by their gender. These findings point to the importance of investigating multiple levels of analysis—not just the school, but also the classroom—in attempting to understand gendered patterns of socioeconomic inequality in education.

Another way to look at the same findings, however, is that students were buffered against the potential negative impact of perceived stereotyping when they had high expectations for success (with the exception of boys from high-SES families). This suggests a potential dynamic interplay between expectations at the personal level and expectations at the societal level (e.g., stereotypes) that can influence adolescents' progress through the math curriculum. It also suggests that it would be fruitful for future research to examine the intersection of policy levers to both improve students' expectations for success in math, as well as to reduce the perception of gender stereotyping in the classroom.

A limitation of these analyses is that they are entirely correlational and cannot shed light on the causal effect of perceptions of classroom stereotyping on adolescents' course-taking decisions in math. Studies that experimentally manipulate classroom stereotypes are therefore a high priority for future research. We return to this discussion in the next chapter.

VII. How The Mindset × Context Perspective Informs Theory and Policy on Educational Inequality

From birth, we humans form mental models—or mindsets—about ourselves and the world around us (Dweck, 2017; Gopnik & Wellman, 2012). By the time we are adolescents starting high school, we have formed rather refined mindsets about our academic skills and educational environments as well as our potential for success (Hecht et al., 2021). That does not mean that our mindsets are fully determinative of our future, however, because we act on our beliefs within the constraints of the opportunities available to us in our contexts. Motivated by this social phenomenon, we attempted to answer in this monograph three key questions about the connections among mindsets, adolescent development, and the modern educational system in the United States. First, how are adolescents' internalized mindsets about their academic skills and preparation (here, expectations for success in math) differentially predictive of academic progress in math across intersectional identity groups? Second, what happens when these mindsets are confronted with school environments that either support or thwart their academic progress? Third, how does the classroom culture—particularly, perceived gender stereotyping about math in the classroom—intersect with these complex patterns of mindsets and gender and socioeconomic inequality?

We answered these questions using the NSLM, the most recent generalizable longitudinal study of youth in the United States, and by applying Mindset × Context Theory, an ecological model of adolescent development. As mentioned previously, Mindset × Context Theory led us to hypothesize that individuals' mindsets (in this case, adolescents' expectations for success in math) would predict positive outcomes most effectively within intersectional identity groups that showed greatest risk for poor performance, in contexts that were not already optimally achieving, and in contexts with supportive, informal peer resources. Using the NSLM data to evaluate these multitiered hypotheses revealed three key findings.

Three Key Findings

First, we learned that *boys from low-SES families were most at risk of not progressing in math early in high school, but that their expectations for success in math were more predictive of math progress than for any other gender-by-SES group*. This finding is consistent with the first tenet of Mindset × Context Theory. It also contributes to the literature on gender stereotyping and its effects on students' educational outcomes. Although girls are subject to anti-female stereotypes in math (e.g., Spencer et al., 1999; Zhao et al., 2022), they did not show the lowest progress in this domain. It was boys—and particularly boys from low-SES families—who did, perhaps due to a perceived conflict between school and anti-intellectual masculine norms (e.g., Hartley & Sutton, 2013; Heyder & Kessels, 2017).

What is notable about this finding is that, although antifemale stereotypes in STEM have been the target of sustained research in developmental psychology for decades, there is much less work on the factors holding back boys from achieving their full potential in school. Our evidence suggests that factors limiting boys' progress are potentially powerful, especially when combined with the structural obstacles that students from low-SES families often encounter. With respect to policymaking, this monograph documents an important developmental antecedent to the later, striking absence of boys from low-SES families from higher education: failure to make progress in math from 9th to 10th grade. Therefore, the monograph highlights a key lever for future policies to consider targeting, perhaps through additional programs or curricular reforms that support boys from low-SES families with low expectations for success in math at this critical juncture.

Second, we learned that *different school contexts powerfully moderated the link between expectations for success in math and math progress*. For all gender and SES intersectional identity groups, the schools with the lowest levels of formal and informal resources (low/medium-achieving schools with unsupportive peer norms) showed a much stronger link between expectations and math progress, relative to schools with the most formal and informal resources (high-achieving schools with supportive peer norms; see Figure 10) As such, the group with the lowest level of math progress was the intersectional identity group at greatest risk (boys from low-SES families with low expectations) in the least-advantaged schools; this group made just 75% of the math progress of students from high-SES families with high-expectations in the most-advantaged schools (Table 17).

One likely reason for this second finding was that low-expectations youth in the most supportive school contexts made progress despite their low expectations. This finding is consistent with a *compensatory* interaction (Miller et al., 2014), in which the resources in a school context appeared to compensate for reduced levels of individual-level psychological resources (i.e., expectations for success). Overall, this second finding yielded mixed evidence with respect to the Mindset × Context Theory predictions. On the one hand, the mindset of high expectations was less essential for students' progress in schools that already had abundant resources, formal and informal, to support math progress, which is consistent with the findings in a previous test of Mindset × Context Theory (Yeager et al., 2019). On the other hand, we did not find that the school's informal resource of peer challenge-seeking norms universally led to a stronger link between expectations for success in math and math progress, which is different from a previous test of Mindset × Context Theory (Yeager et al., 2019). Here, the informal resource of positive, challenge-seeking peer norms appeared to have a compensatory effect—aiding low-expectations youth on the path to math progress—although there were some higher-order interactions in this result across intersectional gender and SES identity groups (see Figure 10).

These findings also contribute an important insight to the psychological literature on expectations and their effects on student achievement. Although expectations reside in an individual's mind, like any psychological variable, their effects come about as a function of how the individual interacts with the opportunities available to them in their broader context (or lack thereof). This insight seems basic, but it is not consistently reflected in most research on the role of mindsets in achievement to date, which tends to measure expectations and achievement while paying less attention to the contexts that students find themselves in as a potential moderator of the relation between these variables. The substantial heterogeneity we observed across contexts (e.g., high- vs. low-resourced schools) in the relation between expectations and progress in math suggests that developmental psychologists who study expectations for success as part of students' motivational frameworks could gain new insights by better incorporating contexts into their studies. In addition, these results provide a solid foundation for future psychological theorizing about *how* contexts shape the relation between expectations and achievement.

Third, we learned that *perceived gender stereotyping in the classroom mattered for the strength of the expectations effects on math progress, but not for boys from high-SES families*. We analyzed students' perceptions that others held gender-biased judgments about math ability, which potentially include the common stereotype that boys are more "naturally" gifted than girls and that girls can achieve in math only with high levels of effort. We suspect that these perceived gender stereotypes may have contributed to the overall differences in expectations for success in math in the NSLM—namely, that boys expected to do better in math in high school than girls, even though girls, in truth, were making more progress. The results for the moderating role of stereotyping were generally consistent with an *accumulated disadvantage* pattern of interaction: groups that perceived negative stereotypes about their math abilities (girls and students from low-SES families), and had low expectations for success in math, were the most likely to have their performance suppressed by the gender stereotyping in the classroom (Figure 13). Although we did not explicitly measure stereotypes related to family background, it may be that gender stereotypes differ for students from low- and high-SES families. Interestingly, the "main effect" of stereotyping extended across the intersectional identity groups, even for boys from high-SES families. Thus, although a classroom with high perceived stereotyping did not magnify the expectations effect for boys from high-SES families, it was nevertheless associated with poorer performance. One reason why is that boys may perceive working hard in math as "girly" (Hartley & Sutton, 2013; Heyder & Kessels, 2017), or they may also be hurt by positive gender stereotypes because the stereotypes assume a "natural" ability in math to which boys may struggle to live up.

This third finding broadens the aperture for Mindset × Context Theory. Most importantly, it includes a performance-suppressing contextual factor—perceived stereotyping—which is different from the potentially performance-enhancing contextual factors in previous studies (school formal and informal resources; Yeager et al., 2019). We found that, in the presence of this negative contextual factor of perceived gender stereotyping, the possible harm coming from a lack of expectations was greater, but the potential benefit of high expectations was not necessarily enhanced. Students in every intersectional identity group had the highest math progress when they had high expectations and were in classrooms with low perceived stereotyping (Table 18). This finding advances theory by showing that, although mindsets can be a partial source of resilience against harmful contexts, adolescents do far better when they have both the internal psychological resource of a positive mindset *and* the contextual resource of a classroom free from gender stereotyping.

For developmental psychologists, these findings also serve as a useful reminder that stereotypes can be harmful even if they are not personally endorsed by the students. The bulk of the developmental literature on gender stereotypes and their relation to student achievement measures students' *own endorsement* of a particular stereotype (e.g., "math = boys") (Cvencek et al., 2011) and then looks for relations between students' endorsement of said stereotype and their achievement, aspirations, and so on. Although personal endorsement is undoubtedly one way in which societal stereotypes suppress the educational outcomes of negatively stereotyped groups (Master et al., 2021), *stereotypes reified by students' educational contexts* (Steele, 1997) are probably at least as powerful, as our monograph makes clear. More research on the relation between gender and racial and ethnic stereotypes and students' achievement in K-12 education should focus on how *contextual* stereotypes shape educational outcomes.

Implications of These Findings

Expectancy-Value Theory

Our research contributes to well-established theories of achievement motivation—most notably, expectancy-value theory. Although the basic association between a student's expectations for success in a domain and their achievement in that domain has been repeatedly documented (e.g., Lauermann et al., 2017), expectancy-value theorists have increasingly begun to acknowledge the complexities in this association (Eccles & Wigfield, 2020). This monograph is the most comprehensive investigation to date of these complexities, which arise at multiple levels. At the individual level, the association between expectations and achievement varies as a function of the individual's complex social identities. Our evidence suggests an SES × Gender pattern of moderation of the association between expectations and achievement in the math domain, and even a potential additional interaction by race/ethnicity. Boys from low-SES families characterized as URG showed the strongest relationships between their expectations for success in math and their math progress between 9th and 10th grade. This evidence answers repeated calls for greater nuance in understanding how the predictive value of expectancy-value constructs differs as a function of students' various identities (e.g., Andersen & Ward, 2014; Lauermann et al., 2017).

Our finding of striking variation in the magnitude of association between expectations and outcomes also has methodological implications, highlighting the importance of including moderators to understand effects. Figure 12 clearly shows that even within the same study, using the same methods, there were many "effects"—the effects for different groups, in different contexts. This finding contradicts the frequent presumption among psychologists that an average effect from a large sample or a meta-analysis should be considered the "true" effect size which has been the basis for claims about the relative importance of different variables in education (Hattie, 2012; Macnamara, 2018). The striking heterogeneity even within the same study (Figure 12) reinforces statistical experts' best practice recommendations, which involve emphasizing the variation or heterogeneity of results, not the average, and refraining from all-or-nothing statements about the importance of effects based on an average (Bryan et al., 2021; Szaszi et al., 2022).

Beyond the individual, this study also powerfully illustrates how the association between expectations and achievement is moderated by contextual factors at different levels (e.g., classroom, school). We found that the association between expectations for success in math and math progress was particularly strong for students in unsupportive contexts (e.g., classrooms with high perceived stereotyping, lower-achieving schools). These results point to expectations for success as a source of resilience—a conclusion that expands the scope of expectancy-value theorizing and is consistent with previous arguments from the neighboring literature on self-efficacy (e.g., Schwarzer & Warner, 2013).

Ecological Perspectives on Inequality

Another take-away message is that psychological orientations alone are likely insufficient to eliminate achievement disparities in early high school math, without also addressing the inequality-promoting forces within schools and classrooms. Although we did find that expectations for success in math predicted math progress, the higher the overall achievement level of schools, the less expectations mattered for students in those schools. In schools with higher achievement levels overall, students had enough resources supporting them that internal motivations were more redundant and less important. That these schools on average also had more students from high-SES families, with all the resources that tend to come with such student bodies, speaks to the cumulative nature of advantages. Expectations matter more when they are among the few resources available to students, but even still, expectations were unlikely, on their own, to overcome the more structural disadvantages students from low-SES families face in their schools. Thus, programs that aim to increase adolescents' confidence, math interest, and expectations for success during high school may help some students but may need to be complemented by other resources to eliminate disparities.

A related take-away of these findings is that *school-level inequalities need to be considered in terms of social climates and not simply structural conditions*. Some school-based peer contexts appeared to enhance low-expectations adolescents' motivations, above and beyond the formal, structural resources in the school. In schools with more peers willing to challenge themselves in math (i.e., higher peer norms), adolescents with low expectations may have felt more comfortable exerting effort in class and taking advanced coursework without facing negative peer attention. Adolescence is a critical time when students look to their peers to determine what behaviors help them fit in (Albert et al., 2013). Consequently, even when adolescents know that behavior does not align with their academic success, they may conform to their peers. Alternatively, behavior is most likely when adolescents know it can promote success and their peers seem to endorse that view. These findings suggest that future studies will be limited if they only focus on the objective and structural resources in the school, without attending to the peer norms. In addition, these findings raise the possibility that peer norms interventions (Cialdini et al., 1991; Paluck & Shepherd, 2012) might be a powerful way to improve the performance of low-expectations youth—especially if they are from groups whose performance has been suppressed.

Teachers and Stereotyping

A final take-away message of these findings for theory and policy is that *training teachers to create classroom cultures conducive to collaborative learning, taking risks, learning from failure, and challenging all students may be a tool for reducing educational inequality and helping students more fully realize their expectations* (Hecht et al., 2021; Murphy et al., 2021). Gendered stereotypes about math achievement from society at large appear to negatively influence *both* boys and girls struggling during the transition to high school. Whether these stereotypes are conveyed to students explicitly or implicitly, adolescents who perceive they are being judged on their performance based on their gender identity may further internalize these stereotypes throughout the rest of their educational careers. Perceiving that people in positions of power confirm their worst fears in school—that they are not good enough, that they are not smart enough, that they will never be able to learn the material—can be influential to students. As prior research using the NSLM found (Yeager et al., 2022), a growth mindset intervention only worked for students when their teachers reported a growth mindset and most likely built a classroom culture that confirms, instead of refutes, the idea that intelligence is malleable and all students from all backgrounds can learn and grow. Improving the beliefs and classroom cultures of teachers, therefore, is a key issue to attend to moving forward, especially for gender and SES groups that are negatively stereotyped.

Study Limitations and Future Directions

Several limitations to this study qualify the strength of the three findings we have highlighted and the take-away messages we have suggested. One key limitation is that our sample was not adequate for understanding racial or ethnic differences in our primary results, which examined cross-school moderation, despite the comparatively large sample size in this research. Therefore, we cannot speak to the complex ways in which racial- and ethnic-based inequality may interact with school informal and formal resources to shape gendered patterns of socioeconomic inequality. Because of the overlap of racial and ethnic and socioeconomic stratification in the United States, young people of color in the United States are more likely to come from socioeconomically disadvantaged circumstances. Yet, because processes of racial and ethnic stratification (e.g., interpersonal discrimination, institutional racism) persist above and beyond socioeconomic stratification, students of color also are less likely to have or be able to capitalize on opportunities for enrollment in advantaged schools and classrooms, even when they are not from socioeconomically disadvantaged circumstances (Kohli et al., 2017; Lewis & Diamond, 2015). Capturing the multiple levels through which structural and interpersonal racism can thwart the expectations of youth from historically underrepresented racial/ethnic groups is critical.

A second limitation is that adolescents' expectations for success in math were measured at high school entry and not before, some adolescents may have already adjusted their expectations during the first few months of high school in relation to their context. If we were to capture expectations before high school entry, we may find even more gaps in adolescents' abilities to translate their expectations for success in math into positive high school math progress. A third limitation is that our measure of expectations was observational, not experimental. Although we included many factors that were related to expectations for success in math (e.g., math interest, math course level in 9th grade, race/ethnicity, and 8th-grade GPA) in the propensity score adjustment that BCF used to address confounding, any causal claim about the link between expectations for success in math and math progress depends on a strict assumption that no additional unmeasured confounders existed, and we cannot confirm this assumption. A fourth limitation is that, although the NSLM measure of peer challenge-seeking norms has been validated by other studies (Rege et al., 2020; Yeager et al., 2019), it is a proxy for peer motivation and engagement in the classroom and school and will have measurement error, like any proxy. For example, students who selected challenging problems for the hypothetical math worksheet task may not have asked for extra work or selected hard problems within their classroom context, and students who regularly challenge themselves in the classroom may not have selected challenging problems for this specific task. A final limitation is that the NSLM measure of perceived classroom gender-based stereotyping did not have a corollary for socioeconomic stereotyping.

These limitations, while not negligible, were also balanced by the many strengths of this study. First, we used the most recent nationally representative sample of 9th graders' mindsets, linked to their administrative outcomes. This allowed us to make generalizable claims about how a psychological variable—expectations for success in math—was related to an outcome of direct policy relevance—math progress. Furthermore, our study was innovative in that it used an interdisciplinary perspective— Mindset × Context Theory—to examine how a mindset variable interacted with multiple moderating factors that have a theoretical basis in the sociological literature—the school's formal resources (achievement level) and informal resources (peer norms, perceived classroom gender stereotyping). We conducted this examination by implementing a state-of-the-art machine-learning algorithm, Bayesian Causal Forest. Using this method, we could interrogate higher-order interactions without raising the possibility of false-positive results that could emerge from fitting dozens of linear models. This method is an advance beyond the common practice in frequentist analysis, and it means that our complex findings are nevertheless trustworthy and serve as a credible basis for building future theory and empirical research.

With both limitations and strengths in mind, this monograph also lays a foundation for future studies. For example, the methods employed here could be used to test whether other mindsets—for instance, about belonging (Walton & Cohen, 2007), relevance (Hulleman & Harackiewicz, 2009), purpose (Yeager et al., 2014), or stress (Crum et al., 2013)—show a similar pattern of results as the present expectations variable. Further, other dimensions of classroom culture—such as a teacher's level of academic press, clarification support, or even relationships of respect (Ferguson & Danielson, 2015)—could be examined in a manner that is similar to the present analysis of perceived stereotyping. The NSLM would be well-suited for all of these analyses, because of its inclusion of rich measures of these student mindsets and classroom context factors and others like them (Yeager et al., 2019).

One particularly exciting extension of the present research will come from the longer-term data from the NSLM that will soon be made publicly available. The schools in the NSLM have been recontacted and re-recruited, and data on high school course-taking and graduation, as well as rich data on college enrollment and voter turnout have been merged. When these data become available to the public, future researchers will be able to examine how different mindsets, at the critical point of the transition to high school, can set young people up for alternate trajectories into adult education and civic participation.

Conclusion

The stakes for building a fair and equitable workforce and society are high, which is why it will be important to build on the foundational research presented here in the coming years. If seemingly small differences in expectations for success in math early in high school—net of actual grades, preparation, and interest in math—can powerfully predict math progress, which is a strong predictor of eventual high school graduation and college matriculation, then developing knowledge of how to either improve expectations or create supportive school structures that help students overcome low expectations could play a meaningful role in making adolescents' transition to adulthood more just and inclusive.

Acknowledgments

The authors would like to thank the former editor of the Monographs, Lynn Liben, for her extensive feedback and support during the initial submission and review process. We would also like to thank our three anonymous reviewers for their engagement with the piece. This paper uses data from the *National Study of Learning Mindsets* (doi: 10.3886/ICPSR37353) (PI: D. Yeager; Co-Is: R. Crosnoe, C. Dweck, C. Muller, B. Schneider, & G. Walton), which was supported by the Raikes Foundation (grant #s 596 and 17-01177), the William T. Grant Foundation (grant #s 189706, 184761, and 182921), the Spencer Foundation (grant # 201500142), the Bezos Family Foundation, the Character Lab, the Houston Endowment, the Bill & Melinda Gates Foundation (grant #s OPP 1197627 and INV-004519), the UBS Optimus Foundation (grant # 47515), the Eunice Kennedy Shriver National Institute of Child Health and Human Development (grant #s P2CHD042849, Population Research Center, T32HD007081, Training Program in Population Studies, and R01HD084772), National Science Foundation (grant #s 1761179 and 2004831), the Yidan Prize Foundation, and an Advanced Research Fellowship from the Jacobs Foundation to D. Yeager. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation, the National Institutes of Health, and other funders.

ORCID

Jamie M. Carroll http://orcid.org/0000-0001-8412-6222
David S. Yeager http://orcid.org/0000-0002-8522-9503
Andrei Cimpian http://orcid.org/0000-0002-3553-6097

References

Adelman, C. (2006). *The toolbox revisited: Paths to degree completion from high school through college*. U.S. Department of Education.

Aiken, L. R. (1991). Detecting, understanding, and controlling for cheating on tests. *Research in Higher Education*, *32*(6), 725–736. https://doi.org/10.1007/BF00974740

Alan, S., Ertac, S., & Mumcu, I. (2018). Gender stereotypes in the classroom and effects on achievement. *The Review of Economics and Statistics*, *100*(5), 876–890. https://doi.org/10.1162/rest_a_00756

Albert, D., Chein, J., & Steinberg, L. (2013). The teenage brain: Peer influences on adolescent decision making. *Current Directions in Psychological Science*, *22*(2), 114–120. https://doi.org/10.1177/0963721412471347

Alexander, K., Entwisle, D., & Olson, L. (2014). *The long shadow: Family background, disadvantaged urban youth, and the transition to adulthood*. Russell Sage Foundation.

Allen, J., Gregory, A., Mikami, A., Lun, J., Hamre, B., & Pianta, R. (2013). Observations of effective teacher–student interactions in secondary school classrooms: Predicting student achievement with the classroom assessment scoring system—secondary. *School Psychology Review*, *42*(1), 76–98. https://doi.org/10.1080/02796015.2013.12087492

Allison, P. D. (2001). *Missing data*. Sage Publications.

Andersen, L., & Ward, T. J. (2014). Expectancy-value models for the STEM persistence plans of ninth-grade, high-ability students: A comparison between Black, Hispanic, and White students. *Science Education*, *98*(2), 216–242. https://doi.org/10.1002/sce.21092

Andersen, S. C., & Nielsen, H. S. (2016). Reading intervention with a growth mindset approach improves children's skills. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(43), 12111–12113. https://doi.org/10.1073/pnas.1607946113

Attewell, P., Lavin, D., Domina, T., & Levey, T. (2007). *Passing the torch: Does higher education for the disadvantaged pay off across the generations?* Russell Sage Foundation.

Autor, D. H. (2014). Skills, education, and the rise of earnings inequality among the "other 99 percent". *Science*, *344*(6186), 843–851.

Bailey, D. H., Duncan, G. J., Cunha, F., Foorman, B. R., & Yeager, D. S. (2020). Persistence and fade-out of educational-intervention effects: Mechanisms and potential solutions. *Psychological Science in the Public Interest*, *21*(2), 55–97. https://doi.org/10.1177/1529100620915848

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147. https://doi.org/10.1037/0003-066X.37.2.122

Barth, J. M., & Masters, S. (2020). Effects of classroom quality, gender stereotypes, and efficacy on math and science interest over school transitions. *International Journal of Gender, Science and Technology*, *12*(1), 4–31.

Beasley, M. A., & Fischer, M. J. (2012). Why they leave: The impact of stereotype threat on the attrition of women and minorities from science, math and engineering majors. *Social Psychology of Education*, *15*(4), 427–448. https://doi.org/10.1007/s11218-012-9185-3

Beilock, S. L., Gunderson, E. A., Ramirez, G., & Levine, S. C. (2010). Female teachers' math anxiety affects girls' math achievement. *Proceedings of the National Academy of Sciences of the United States of America*, *107*, 1860–1863. https://doi.org/10.1073/pnas.0910967107

Belkin, D. (2021). A generation of American men give up on college: 'I Just Feel Lost'. Wall Street Journal. https://www.wsj.com/articles/college-university-fall-higher-education-men-women-enrollment-admissions-back-to-school-11630948233

Benner, A. D., & Graham, S. (2009). The transition to high school as a developmental process among multiethnic urban youth. *Child Development*, *80*(2), 356–376. https://doi.org/10.1111/j.1467-8624.2009.01265.x

Bigler, R. S., & Liben, L. S. (2006). A developmental intergroup theory of social stereotypes and prejudice. *Advances in Child Development and Behavior*, *34*, 39–89.

Black, S. E., Muller, C., Spitz-Oener, A., He, Z., Hung, K., & Warren, J. R. (2021). The importance of STEM: High school knowledge, skills and occupations in an era of growing inequality. *Research Policy*, *50*(7), 104249.

Bozick, R., Alexander, K., Entwisle, D., Dauber, S., & Kerr, K. (2010). Framing the future: Revisiting the place of educational expectations in status attainment. *Social Forces*, *88*(5), 2027–2052. https://doi.org/10.1353/sof.2010.0033

Breda, T., Jouini, E., Napp, C., & Thebault, G. (2020). Gender stereotypes can explain the gender-equality paradox. *Proceedings of the National Academy of Sciences of thr United States of America*, *117*(49), 31063–31069. https://doi.org/10.1073/pnas.2008704117

Bronfenbrenner, U. (1981). *The ecology of human development: Experiments by nature and design*. Harvard University Press.

Bryan, C. J., Tipton, E., & Yeager, D. S. (2021). Behavioural science is unlikely to change the world without a heterogeneity revolution. *Nature Human Behaviour*, *5*(8), 980–989. https://doi.org/10.1038/s41562-021-01143-3

Bryk, A. S., & Schneider, B. (2003). Trust in schools: A core resource for school reform. *Educational Leadership*, *60*(6), 40–45.

Buchmann, C., DiPrete, T. A., & McDaniel, A. (2008). Gender inequalities in education. *Annual Review of Sociology*, *34*(1), 319–337. https://doi.org/10.1146/annurev.soc.34.040507.134719

Budig, M. J., Lim, M., & Hodges, M. J. (2021). Racial and gender pay disparities: The role of education. *Social Science Research*, *98*, 102580.

Carroll, J. M., Muller, C., Grodsky, E., & Warren, J. R. (2017). Tracking health inequalities from high school to midlife. *Social Forces*, *96*(2), 591–628. https://doi.org/10.1093/sf/sox065

Carter, P. L. (2018). Education's limitations and its radical possibilities. *Contexts*, *17*(2), 22–27. https://doi.org/10.1177/1536504218776956

Chetty, R., Hendren, N., Kline, P., Saez, E., & Turner, N. (2014). Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *American Economic Review*, *104*(5), 141–147. https://doi.org/10.1257/aer.104.5.141

Chin, M. J., Quinn, D. M., Dhaliwal, T. K., & Lovison, V. S. (2020). Bias in the air: A nationwide exploration of teachers' implicit racial attitudes, aggregate bias, and student outcomes. *Educational Researcher*, *49*(8), 566–578.

Chipman, H. A., George, E. I., & McCulloch, R. E. (2010). BART: Bayesian additive regression trees. *The Annals of Applied Statistics*, *4*(1), 266–298. https://doi.org/10.1214/09-AOAS285

Choo, H. Y., & Ferree, M. M. (2010). Practicing intersectionality in sociological research: A critical analysis of inclusions, interactions, and institutions in the study of inequalities. *Sociological Theory*, *28*(2), 129–149. https://doi.org/10.1111/j.1467-9558.2010.01370.x

Choukas-Bradley, S., Giletta, M., Widman, L., Cohen, G. L., & Prinstein, M. J. (2014). Experimentally measured susceptibility to peer influence and adolescent sexual behavior trajectories: A preliminary study. *Developmental Psychology*, *50*(9), 2221–2227. https://doi.org/10.1037/a0037300

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. *Advances in Experimental Social Psychology*, *24*, 201–234.

Cimpian, A., Mu, Y., & Erickson, L. C. (2012). Who is good at this game? Linking an activity to a social category undermines children's achievement. *Psychological Science*, *23*(5), 533–541. https://doi.org/10.1177/0956797611429803

Cimpian, A., & Salomon, E. (2014). The inherence heuristic: An intuitive means of making sense of the world, and a potential precursor to psychological essentialism. *Behavioral and Brain Sciences*, *37*(5), 461–480. https://doi.org/10.1017/S0140525X13002197

Clark, K. B., & Clark, M. P. (1947). Racial identification and preference in negro children. In *Readings in social psychology* (pp. 169–178). Henry Holt and Company.

Coleman, J. S. (1961). *The adolescent society* (p. xvi, 368). Free Press of Glencoe.

Coleman, J. S., & Hoffer, T. (1987). *Public and private high schools: The impact of communities*. Basic Books.

Conger, D., & Long, M. C. (2010). Why are men falling behind? Gender gaps in college performance and persistence. *The Annals of the American Academy of Political and Social Science*, *627*(1), 184–214. https://doi.org/10.1177/0002716209348751

Crosnoe, R. (2009). Low-income students and the socioeconomic composition of public high schools. *American Sociological Review*, *74*(5), 709–730. https://doi.org/10.1177/000312240907400502

Crosnoe, R. (2011). *Fitting in, standing out: Navigating the social challenges of high school to get an education*. Cambridge University Press.

Crosnoe, R., & Huston, A. C. (2007). Socioeconomic status, schooling, and the developmental trajectories of adolescents. *Developmental Psychology*, *43*(5), 1097.

Crosnoe, R., & Muller, C. (2014). Family socioeconomic status, peers, and the path to college. *Social Problems*, *61*(4), 602–624. https://doi.org/10.1525/sp.2014.12255

Crosnoe, R., Riegle-Crumb, C., Field, S., Frank, K., & Muller, C. (2008). Peer group contexts of girls' and boys' academic experiences. *Child Development*, *79*(1), 139–155. https://doi.org/10.1111/j.1467-8624.2007.01116.x

Crosnoe, R., & Schneider, B. (2010). Social capital, information, and socioeconomic disparities in math course work. *American Journal of Education*, *117*(1), 79–107. https://doi.org/10.1086/656347

Crum, A. J., Jamieson, J. P., & Akinola, M. (2020). Optimizing stress: An integrated intervention for regulating stress responses. *Emotion*, *20*(1), 120–125. https://doi.org/10.1037/emo0000670

Crum, A. J., Salovey, P., & Achor, S. (2013). Rethinking stress: The role of mindsets in determining the stress response. *Journal of Personality and Social Psychology*, *104*(4), 716–733. https://doi.org/10.1037/a0031201

Cvencek, D., Meltzoff, A. N., & Greenwald, A. G. (2011). Math–gender stereotypes in elementary school children. *Child Development*, *82*(3), 766–779.

Dahl, R. E., Allen, N. B., Wilbrecht, L., & Suleiman, A. B. (2018). Importance of investing in adolescence from a developmental science perspective. *Nature*, *554*(7693), 441–450. https://doi.org/10.1038/nature25770

Damon, W., Menon, J., & Bronk, K. C. (2003). The development of purpose during adolescence. *Applied Developmental Science*, *7*(3), 119–128. https://doi.org/10.1207/S1532480XADS0703_2

Destin, M., Hanselman, P., Buontempo, J., Tipton, E., & Yeager, D. S. (2019). Do student mindsets differ by socioeconomic status and explain disparities in academic achievement in the United States? *AERA Open*, *5*(3), 1–12. https://doi.org/10.1177/2332858419857706

DiPrete, T. A., & Buchmann, C. (2013). *The rise of women: The growing gender gap in education and what it means for American schools*. Russell Sage Foundation.

Domina, T., Penner, A., & Penner, E. (2017). Categorical inequality: Schools as sorting machines. *Annual Review of Sociology*, *43*, 311–330.

Domina, T., & Saldana, J. (2012). Does raising the bar level the playing field?: Mathematics curricular intensification and inequality in american high schools, 1982–2004. *American Educational Research Journal*, *49*(4), 685–708. https://doi.org/10.3102/0002831211426347

Dorie, V., Hill, J., Shalit, U., Scott, M., & Cervone, D. (2019). Automated versus do-it-yourself methods for causal inference: Lessons learned from a data analysis competition. *Statistical Science*, *34*(1), 43–68. https://doi.org/10.1214/18-STS667

Douglas, D., & Attewell, P. (2017). School mathematics as gatekeeper. *The Sociological Quarterly*, *58*(4), 648–669. https://doi.org/10.1080/00380253.2017.1354733

Downey, D. B., & Condron, D. J. (2016). Fifty years since the Coleman Report: Rethinking the relationship between schools and inequality. *Sociology of Education*, *89*(3), 207–220. https://doi.org/10.1177/0038040716651676

Duncan, G. J., & Murnane, R. J. (2011). *Whither opportunity?: Rising inequality, schools, and children's life chances*. Russell Sage Foundation.

Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.

Dweck, C. S. (2017). From needs to goals and representations: Foundations for a unified theory of motivation, personality, and development. *Psychological Review*, *124*(6), 689–719. https://doi.org/10.1037/rev0000082

Dweck, C. S., & Yeager, D. S. (2019). Mindsets: A view from two eras. *Perspectives on Psychological Science*, *14*(3), 481–496. https://doi.org/10.1177/1745691618804166

Eccles, J. S. (2005). Studying gender and ethnic differences in participation in math, physical science, and information technology. *New Directions for Child and Adolescent Development*, *2005*(110), 7–14. https://doi.org/10.1002/cd.146

Eccles, J. S. (2009). Who am I and what am I going to do with my life? Personal and collective identities as motivators of action. *Educational Psychologist*, *44*(2), 78–89. https://doi.org/10.1080/00461520902832368

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Eccles, J. S., & Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology*, *72*(1), 218.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology*, *54*(1), 5–12. https://doi.org/10.1037//0022-3514.54.1.5

Fahle, E. M., Reardon, S. F., Kalogrides, D., Weathers, E. S., & Jang, H. (2020). Racial segregation and school poverty in the United States, 1999–2016. *Race and Social Problems*, *12*(1), 42–56. https://doi.org/10.1007/s12552-019-09277-w

Ferguson, R. F., & Danielson, C. (2015). How framework for teaching and Tripod 7Cs evidence distinguish key components of effective teaching. In T. J. Kane, K. A. Kerr, & R. C. Pianta (Eds.), *Designing teacher evaluation systems* (pp. 98–143). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781119210856.ch4

Fischer, C. S., & Hout, M. (2006). *Century of difference*. Russell Sage Foundation.

Foley, A. E., Herts, J. B., Borgonovi, F., Guerriero, S., Levine, S. C., & Beilock, S. L. (2017). The math anxiety-performance link: A global phenomenon. *Current Directions in Psychological Science*, *26*(1), 52–58. https://doi.org/10.1177/0963721416672463

Frank, K. A., Muller, C., Schiller, K. S., Riegle-Crumb, C., Mueller, A. S., Crosnoe, R., & Pearson, J. (2008). The social dynamics of mathematics coursetaking in high school. *American Journal of Sociology*, *113*(6), 1645–1696. https://doi.org/10.1086/587153

Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper). *Bayesian Analysis*, *1*(3), 515–534. https://doi.org/10.1214/06-BA117A

Gopalan, M., & Tipton, E. (2018). *Is the national study of learning mindsets nationally-representative?* https://Psyarxiv.Com/Dvmr7/

Gopnik, A., & Wellman, H. M. (2012). Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory. *Psychological Bulletin*, *138*(6), 1085–1108. https://doi.org/10.1037/a0028044

Gordon, R. A., Crosnoe, R., & Wang, X. (2013). Physical attractiveness and the accumulation of social and human capital in adolescence and young adulthood: Assets and distractions. *Monographs of the Society for Research in Child Development*, *78*(6), 1–137. https://doi.org/10.1002/mono.12060

Hahn, P. R., Carvalho, C. M., Puelz, D., & He, J. (2018). Regularization and Confounding in Linear Regression for Treatment Effect Estimation. *Bayesian Analysis*, *13*(1), 163–182. https://doi.org/10.1214/16-BA1044

Hahn, P. R., Dorie, V., & Murray, J. S. (2019). Atlantic causal inference conference (ACIC) data analysis challenge 2017. *ArXiv Preprint. ArXiv:1905.09515*.

Hahn, P. R., Murray, J. S., & Carvalho, C. M. (2020). Bayesian regression tree models for causal inference: Regularization, confounding, and heterogeneous effects. *Bayesian Analysis*, *15*(3), 965–1056. https://doi.org/10.1214/19-BA1195

Hanselman, P., & Fiel, J. E. (2017). School opportunity hoarding? Racial segregation and access to high growth schools. *Social Forces*, *95*(3), 1077–1104. https://doi.org/10.1093/sf/sow088

Harackiewicz, J. M., Canning, E. A., Tibbetts, Y., Priniski, S. J., & Hyde, J. S. (2016). Closing achievement gaps with a utility-value intervention: Disentangling race and social class. *Journal of Personality and Social Psychology*, *111*, 745–765. https://doi.org/10.1037/pspp0000075

Harter, S., & Pike, R. (1984). The pictorial scale of perceived competence and social acceptance for young children. *Child Development*, *55*(6), 1969–1982. https://doi.org/10.2307/1129772

Hartley, B. L., & Sutton, R. M. (2013). A stereotype threat account of boys' academic underachievement. *Child Development*, *84*(5), 1716–1733. https://doi.org/10.1111/cdev.12079

Hattie, J. (2012). *Visible learning for teachers: Maximizing impact on learning*. Routledge.

Hecht, C. A., Dweck, C. S., Murphy, M. C., Kroeper, K. M., & Yeager, D. S. (2023). Efficiently exploring the causal role of contextual moderators in behavioral science. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(1), e2216315120. https://doi.org/10.1073/pnas.2216315120

Hecht, C. A., Yeager, D. S., Dweck, C. S., & Murphy, M. C. (2021). Beliefs, affordances, and adolescent development: Lessons from a decade of growth mindset interventions. In J. J. Lockman (Ed.), *Advances in child development and behavior* (Vol. 61, pp. 169–197). JAI. https://doi.org/10.1016/bs.acdb.2021.04.004

Helms, S. W., Choukas-Bradley, S., Widman, L., Giletta, M., Cohen, G. L., & Prinstein, M. J. (2014). Adolescents misperceive and are influenced by high-status peers' health risk, deviant, and adaptive behavior. *Developmental Psychology*, *50*(12), 2697–2714. https://doi.org/10.1037/a0038178

Heyder, A., & Kessels, U. (2013). Is school feminine? Implicit gender stereotyping of school as a predictor of academic achievement. *Sex Roles*, *69*(11), 605–617. https://doi.org/10.1007/s11199-013-0309-9

Heyder, A., & Kessels, U. (2017). Boys Don't Work? On the Psychological Benefits of Showing Low Effort in High School. *Sex Roles*, *77*(1), 72–85. https://doi.org/10.1007/s11199-016-0683-1

Hill, J., Linero, A., & Murray, J. (2020). Bayesian Additive Regression Trees: A Review and Look Forward. *Annual Review of Statistics and Its Application*, *7*(1), 251–278. https://doi.org/10.1146/annurev-statistics-031219-041110

Hill, P. L., Burrow, A. L., Brandenberger, J. W., Lapsley, D. K., & Quaranto, J. C. (2010). Collegiate purpose orientations and well-being in early and middle adulthood. *Journal of Applied Developmental Psychology*, *31*(2), 173–179. https://doi.org/10.1016/j.appdev.2009.12.001

Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology*, *38*(1), 379–400. https://doi.org/10.1146/annurev.soc.012809.102503

Hulleman, C. S., & Harackiewicz, J. M. (2009). Promoting interest and performance in high school science classes. *Science*, *326*(5958), 1410–1412. https://doi.org/10.1126/science.1177067

Ingels, S. J., Pratt, D. J., Herget, D. R., Bryan, M., Fritch, L. B., Ottem, R., Rogers, J. E., & Wilson, D. (2015). *High school longitudinal study of 2009 (HSLS: 09) 2013 update and high school transcript* (p. 154).

Institute of Education Sciences. (2020). *The condition of education 2020*. Institute of Education Sciences. https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2020144

Irizarry, Y. (2021). On track or derailed? Race, advanced math, and the transition to high school. *Socius*, *7*, 2378023120980293. https://doi.org/10.1177/2378023120980293

Jiang, S., Simpkins, S. D., & Eccles, J. S. (2020). Individuals' math and science motivation and their subsequent STEM choices and achievement in high school and college: A longitudinal study of gender and college generation status differences. *Developmental Psychology*, *56*(11), 2137–2151. https://doi.org/10.1037/dev0001110

Kalev, A. (2014). How you downsize is who you downsize: Biased formalization, accountability, and managerial diversity. *American Sociological Review*, *79*(1), 109–135.

King, D. K. (1988). Multiple jeopardy, multiple consciousness: The context of a Black feminist ideology. *Signs: Journal of Women in Culture and Society*, *14*(1), 42–72.

Kohli, R., Pizarro, M., & Nevárez, A. (2017). The "New Racism" of K–12 Schools: Centering Critical Research on Racism. *Review of Research in Education*, *41*(1), 182–202. https://doi.org/10.3102/0091732X16686949

Langenkamp, A. G. (2010). Academic vulnerability and resilience during the transition to high school: The role of social relationships and district context. *Sociology of Education*, *83*(1), 1–19. https://doi.org/10.1177/0038040709356563

Lareau, A. (2011). *Unequal childhoods: Class, race, and family life*. University of California Press.

Lauermann, F., Tsai, Y.-M., & Eccles, J. (2017). Math-related career aspirations and choices within Eccles et al's expectancy–value theory of achievement-related behaviors. *Developmental Psychology*, *53*(8), 1540–1559. https://doi.org/10.1037/dev0000367

Leslie, S.-J., Cimpian, A., Meyer, M., & Freeland, E. (2015). Expectations of brilliance underlie gender distributions across academic disciplines. *Science*, *347*(6219), 262–265. https://doi.org/10.1126/science.1261375

Lewis, A. E., & Diamond, J. B. (2015). *Despite the best intentions: How racial inequality thrives in good schools*. Oxford University Press.

Liaw, A., Wiener, M., Breiman, L., & Cutler, A. (2015). Package 'randomForest'.

Lucas, S. R. (2001). Effectively maintained inequality: Education transitions, track mobility, and social background effects. *American Journal of Sociology*, *106*(6), 1642–1690. https://doi.org/10.1086/321300

Macnamara, B. (2018). *Schools are buying "growth mindset" interventions despite scant evidence that they work well*. The Conversation. http://theconversation.com/schools-are-buying-growth-mindset-interventions-despite-scant-evidence-that-they-work-well-96001

Marsh, H. W. (1990). The structure of academic self-concept: The Marsh/Shavelson model. *Journal of Educational Psychology*, *82*(4), 623–636. https://doi.org/10.1037/0022-0663.82.4.623

Master, A., Meltzoff, A. N., & Cheryan, S. (2021). Gender stereotypes about interests start early and cause gender disparities in computer science and engineering. *Proceedings of the National Academy of Sciences*, *118*(48), e2100030118.

McConnell, K. J., & Lindner, S. (2019). Estimating treatment effects with machine learning. *Health Services Research*, *54*(6), 1273–1282. https://doi.org/10.1111/1475-6773.13212

McGrew, W. (2019). U.S. school segregation in the 21st century. Equitable Growth. http://www.equitablegrowth.org/research-paper/u-s-school-segregation-in-the-21st-century/

Meyer, M., Cimpian, A., & Leslie, S.-J. (2015). Women are underrepresented in fields where success is believed to require brilliance. *Frontiers in Psychology*, *6*, 235. https://doi.org/10.3389/fpsyg.2015.00235

Mijs, J. J. B., & Roe, E. L. (2021). Is America coming apart? Socioeconomic segregation in neighborhoods, schools, workplaces, and social networks, 1970–2020. *Sociology Compass*, *15*(6), e12884. https://doi.org/10.1111/soc4.12884

Miller, D. I., Eagly, A. H., & Linn, M. C. (2015). Women's representation in science predicts national gender-science stereotypes: Evidence from 66 nations. *Journal of Educational Psychology*, *107*(3), 631–644. https://doi.org/10.1037/edu0000005

Miller, E. B., Farkas, G., Vandell, D. L., & Duncan, G. J. (2014). Do the effects of head start vary by parental preacademic stimulation? *Child Development*, *85*(4), 1385–1400. https://doi.org/10.1111/cdev.12233

Morgan, S. L. (2005). *On the edge of commitment: Educational attainment and race in the United States*. Stanford University Press.

Mouw, T., & Kalleberg, A. L. (2010). Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s. *American Sociological Review*, *75*(3), 402–431. https://doi.org/10.1177/0003122410363564

Muenks, K., Wigfield, A., & Eccles, J. S. (2018). I can do this! The development and calibration of children's expectations for success and competence beliefs. *Developmental Review*, *48*, 24–39. https://doi.org/10.1016/j.dr.2018.04.001

Murphy, M. C., Fryberg, S. A., Brady, L. M., Canning, E. A., & Hecht, C. A. (2021). *Global mindset initiative paper 1: Growth mindset cultures and teacher practices*. Yidan Prize Foundation.

Murphy, M. C., Gopalan, M., Carter, E. R., Emerson, K. T. U., Bottoms, B. L., & Walton, G. M. (2020). A customized belonging intervention improves retention of socially disadvantaged students at a broad-access university. *Science Advances*, *6*, eaba4677. https://doi.org/10.1126/sciadv.aba4677

National Forum on Education Statistics. (2014). *Forum guide to school courses for the exchange of data (SCED) classification system*. U.S. Department of Education. National Center for Education Statistics.

National Science Foundation. (2020). *Stem education for the future: A visioning report*.

Nosek, B. A., Smyth, F., Sriram, N., Lindner, N., Devos, T., Ayala, A., Bar-Anan, Y., Bergh, R., Cai, H., Gonsalkorale, K., Kesebir, S., Maliszewski, N., Neto, F., Olli, E., Park, J., Schnabel, K., Shiomura, K., Tudor Tulbure, B., Wiers, R., … Greenwald, A. (2009). National differences in gender–science stereotypes predict national sex differences in science and math achievement. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(26), 10593–10597. https://doi.org/10.1073/pnas.0809921106

Paluck, E. L., & Shepherd, H. (2012). The salience of social referents: A field experiment on collective norms and harassment behavior in a school social network. *Journal of Personality and Social Psychology*, *103*(6), 899–915. https://doi.org/10.1037/a0030015

Paschall, K. W., Gershoff, E. T., & Kuhfeld, M. (2018). A two decade examination of historical race/ethnicity disparities in academic achievement by poverty status. *Journal of Youth and Adolescence*, *47*(6), 1164–1177. https://doi.org/10.1007/s10964-017-0800-7

Penner, A. M. (2015). Gender inequality in science. *Science*, *347*(6219), 234–235. https://doi.org/10.1126/science.aaa3781

Penner, A. M., & Paret, M. (2008). Gender differences in mathematics achievement: Exploring the early grades and the extremes. *Social Science Research*, *37*(1), 239–253. https://doi.org/10.1016/j.ssresearch.2007.06.012

Porter, T., Molina, D., Cimpian, A., Roberts, S., Fredericks, A., Blackwell, L., & Trzesniewski, K. (2021). Growth mindset intervention delivered by teachers boosts achievement in early adolescence. *Psychological Science*, *33*, 1086–1096.

Quillian, L. (2014). Does segregation create winners and losers? Residential segregation and inequality in educational attainment. *Social Problems*, *61*(3), 402–426. https://doi.org/10.1525/sp.2014.12193

Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. In G. J. Duncan & R. J. Murnane (Eds.), *Whither opportunity?: Rising inequality, schools, and children's life chances* (pp. 91–116). Russell Sage Foundation.

Reardon, S. F., Fahle, E. M., Kalogrides, D., Podolsky, A., & Zárate, R. C. (2019). Gender achievement gaps in U.S. school districts. *American Educational Research Journal*, *56*(6), 2474–2508. https://doi.org/10.3102/0002831219843824

Reardon, S. F., & Robinson, J. P. (2008). Patterns and trends in racial/ethnic and socioeconomic academic achievement gaps. *Handbook of Research in Education Finance and Policy* (pp. 497–516). Taylor and Francis.

Reeves, S. L., Henderson, M. D., Cohen, G. L., Steingut, R. R., Hirschi, Q., & Yeager, D. S. (2020). Psychological affordances help explain where a self-transcendent purpose intervention improves performance. *Journal of Personality and Social Psychology*, *120*, 1–15. https://doi.org/10.1037/pspa0000246

Rege, M., Hanselman, P., Solli, I. F., Dweck, C. S., Ludvigsen, S., Bettinger, E., Crosnoe, R., Muller, C., Walton, G., Duckworth, A., & Yeager, D. S. (2020). How can we inspire nations of learners?

An investigation of growth mindset and challenge-seeking in two countries. *American Psychologist*, *76*, 755–767. https://doi.org/10.1037/amp0000647

Riegle-Crumb, C. (2006). The path through math: Course sequences and academic performance at the intersection of race-ethnicity and gender. *American Journal of Education*, *113*(1), 101–122. https://doi.org/10.1086/506495

Riegle-Crumb, C., & Grodsky, E. (2010). Racial-ethnic differences at the intersection of math course-taking and achievement. *Sociology of Education*, *83*(3), 248–270. https://doi.org/10.1177/0038040710375689

Riegle-Crumb, C., & Humphries, M. (2012). Exploring bias in math teachers' perceptions of students' ability by gender and race/ethnicity. *Gender & Society*, *26*(2), 290–322. https://doi.org/10.1177/0891243211434614

Riegle-Crumb, C., Kyte, S. B., & Morton, K. (2018). Gender and racial/ethnic differences in educational outcomes: Examining patterns, explanations, and new directions for research. In B. Schneider (Ed.), *Handbook of the Sociology of Education in the 21st Century* (pp. 131–152). Springer International Publishing. https://doi.org/10.1007/978-3-319-76694-2_6

Riegle-Crumb, C., & Morton, K. (2017). Gendered expectations: Examining how peers shape female students' intent to pursue stem fields. *Frontiers in Psychology*, *8*, 329. https://doi.org/10.3389/fpsyg.2017.00329

Riegle-Crumb, C., & Peng, M. (2021). Examining high school students' gendered beliefs about math: Predictors and implications for choice of stem college majors. *Sociology of Education*, *94*(3), 227–248. https://doi.org/10.1177/00380407211014777

Rogers, T., & Feller, A. (2016). Discouraged by peer excellence: Exposure to exemplary peer performance causes quitting. *Psychological Science*, *27*(3), 365–374.

Rose, H., & Betts, J. R. (2004). The effect of high school courses on earnings. *The Review of Economics and Statistics*, *86*(2), 497–513. https://doi.org/10.1162/003465304323031076

Saujani, R. (2017). *Girls who code: Learn to code and change the world*. Penguin.

Schiller, K. S. (1999). Effects of feeder patterns on students' transition to high school. *Sociology of Education*, *72*(4), 216–233. https://doi.org/10.2307/2673154

Schneider, B., & Stevenson, D. (1999). *The ambitious generation: America's teenagers, motivated but directionless*. Yale University Press.

Schunk, D. H., & DiBenedetto, M. K. (2021). Chapter four—Self-efficacy and human motivation. In A. J. Elliot (Ed.), *Advances in Motivation Science* (Vol. 8, pp. 153–179). Elsevier. https://doi.org/10.1016/bs.adms.2020.10.001

Schwarzer, R., & Warner, L. M. (2013). Perceived self-efficacy and its relationship to resilience. In S. Prince-Embury & D. Saklofske (Eds.), *Resilience in children, adolescents, and adults* (pp. 139–150). Springer.

Sharkey, P. (2013). *Stuck in place: Urban neighborhoods and the end of progress toward racial equality*. University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/S/bo14365260.html

Spencer, S. J., Steele, C. M., & Quinn, D. M. (1999). Stereotype threat and women's math performance. *Journal of Experimental Social Psychology*, *35*(1), 4–28. https://doi.org/10.1006/jesp.1998.1373

Starling, J. E., Murray, J. S., Carvalho, C. M., Bukowski, R. K., & Scott, J. G. (2020). Bart with targeted smoothing: An analysis of patient-specific stillbirth risk. *Annals of Applied Statistics*, *14*(1), 28–50.

Starling, J. E., Murray, J. S., Lohr, P. A., Aiken, A. R. A., Carvalho, C. M., & Scott, J. G. (2020). Targeted smooth Bayesian causal forests: An analysis of heterogeneous treatment effects for simultaneous versus interval medical abortion regimens over gestation. *ArXiv:1905.09405 [Stat]*. http://arxiv.org/abs/1905.09405

Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist*, *52*(6), 613–629. https://doi.org/10.1037/0003-066X.52.6.613

Stephens, N. M., Markus, H. R., & Phillips, L. T. (2014). Social class culture cycles: How three gateway contexts shape selves and fuel inequality. *Annual Review of Psychology*, *65*(1), 611–634. https://doi.org/10.1146/annurev-psych-010213-115143

Stinebrickner, R., & Stinebrickner, T. (2014). Academic performance and college dropout: Using longitudinal expectations data to estimate a learning model. *Journal of Labor Economics*, *32*(3), 601–644. https://doi.org/10.1086/675308

Szaszi, B., Higney, A., Charlton, A., Gelman, A., Ziano, I., Aczel, B., Goldstein, D. G., Yeager, D. S., & Tipton, E. (2022). No reason to expect large and consistent effects of nudge interventions. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(31), e2200732119. https://doi.org/10.1073/pnas.2200732119

Tipton, E. (2014). How generalizable is your experiment? An index for comparing experimental samples and populations. *Journal of Educational and Behavioral Statistics*, *39*(6), 478–501. https://doi.org/10.3102/1076998614558486

Tipton, E., Yeager, D. S., Iachan, R., & Schneider, B. (2019). Designing probability samples to study treatment effect heterogeneity. In P. J. Lavrakas (Ed.), *Experimental methods in survey research: Techniques that combine random sampling with random assignment* (pp. 435–456). Wiley. https://doi.org/10.1002/9781119083771.ch22

Tyson, W., & Roksa, J. (2016). How schools structure opportunity: The role of curriculum and placement in math attainment. *Research in Social Stratification and Mobility*, *44*, 124–135. https://doi.org/10.1016/j.rssm.2016.04.003

Walton, G. M., & Cohen, G. L. (2003). Stereotype lift. *Journal of Experimental Social Psychology*, *39*, 456–467. https://doi.org/10.1016/S0022-1031(03)00019-2

Walton, G. M., & Cohen, G. L. (2007). A question of belonging: Race, social fit, and achievement. *Journal of Personality and Social Psychology*, *92*(1), 82–96. https://doi.org/10.1037/0022-3514.92.1.82

Walton, G. M., & Cohen, G. L. (2011). A brief social-belonging intervention improves academic and health outcomes of minority students. *Science*, *331*(6023), 1447–1451. https://doi.org/10.1126/science.1198364

Walton, G. M., Logel, C., Peach, J. M., Spencer, S. J., & Zanna, M. P. (2015). Two brief interventions to mitigate a "chilly climate" transform women's experience, relationships, and achievement in engineering. *Journal of Educational Psychology*, *107*(2), 468–485.

Walton, G. M., Murphy, M. C., Logel, C., Yeager, D. S., Goyer, J. P., Brady, S. T., Paunesku, D., Fotuhi, O., Blodorn, A., Boucher, K. L., Carter, E. R., Gopalan, M., Henderson, A., Kroeper, K. M., Murdock-Perriera, L. A., Ablorh, T., Chen, S., Fisher, P., Galvan, M., … Krol, N. (2023). Where and with whom does a brief social-belonging intervention promote progress in college? *Science*. *380*(664): 499–505.

Walton, G. M., & Wilson, T. D. (2018). Wise interventions: Psychological remedies for social and personal problems. *Psychological Review*, *125*(5), 617–655. https://doi.org/10.1037/rev0000115

Walton, G. M., & Yeager, D. S. (2020). Seed and soil: Psychological affordances in contexts help to explain where wise interventions succeed or fail. *Current Directions in Psychological Science*, *29*(3), 219–226. https://doi.org/10.1177/0963721420904453

Warren, E., & Supreme Court Of The United States. (1953). *U.S. reports: Brown v. Board of Education (347 U.S. 483)*. The Library of Congress. https://www.loc.gov/item/usrep347483/

Weininger, E. B., Lareau, A., & Conley, D. (2015). What money doesn't buy: Class resources and children's participation in organized extracurricular activities. *Social Forces*, *94*(2), 479–503. https://doi.org/10.1093/sf/sov071

Wendling, T., Jung, K., Callahan, A., Schuler, A., Shah, N., & Gallego, B. (2018). Comparing methods for estimation of heterogeneous treatment effects using observational data from health care databases. *Statistics in Medicine*, *37*(23), 3309–3324. https://doi.org/10.1002/sim.7820

Wentzel, K. R. (1999). Social-motivational processes and interpersonal relationships: Implications for understanding motivation at school. *Journal of Educational Psychology*, *91*, 76–97. https://doi.org/10.1037/0022-0663.91.1.76

Wentzel, K. R., & Looney, L. (2007). Socialization in school settings. In J. E. Grusec & P. D. Hastings (Eds.), *Handbook of socialization: Theory and research* (pp. 382–403). The Guilford Press.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Woody, S., Carvalho, C. M., & Murray, J. S. (2021). Model interpretation through lower-dimensional posterior summarization. *Journal of Computational and Graphical Statistics*, *30*(1), 144–161. https://doi.org/10.1080/10618600.2020.1796684

Yeager, D. S., & Bundick, M. J. (2009). The role of purposeful work goals in promoting meaning in life and in schoolwork during adolescence. *Journal of Adolescent Research*, *24*(4), 423–452.

Yeager, D. S., Carroll, J. M., Buontempo, J., Cimpian, A., Woody, S., Crosnoe, R., Muller, C., Murray, J., Mhatre, P., Kersting, N., Hulleman, C., Kudym, M., Murphy, M., Duckworth, A. L., Walton, G. M., & Dweck, C. S. (2022). Teacher mindsets help explain where a growth-mindset intervention does and doesn't work. *Psychological Science*, *33*(1), 18–32. https://doi.org/10.1177/09567976211028984

Yeager, D. S., Dahl, R. E., & Dweck, C. S. (2018). Why interventions to influence adolescent behavior often fail but could succeed. *Perspectives on Psychological Science*, *13*(1), 101–122. https://doi.org/10.1177/1745691617722620

Yeager, D. S., & Dweck, C. S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist*, *47*(4), 302–314. https://doi.org/10.1080/00461520.2012.722805

Yeager, D. S., & Dweck, C. S. (2020). What can be learned from growth mindset controversies? *American Psychologist*, *75*, 1269–1284. https://doi.org/10.1037/amp0000794

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., … Dweck, C. S. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, *573*(7774), 364–369. https://doi.org/10.1038/s41586-019-1466-y

Yeager, D. S., Henderson, M. D., Paunesku, D., Walton, G. M., D'Mello, S., Spitzer, B. J., & Duckworth, A. L. (2014). Boring but important: A self-transcendent purpose for learning fosters academic self-regulation. *Journal of Personality and Social Psychology*, *107*(4), 559–580. https://doi.org/10.1037/a0037637

Yeager, D. S., Walton, G. M., Brady, S. T., Akcinar, E. N., Paunesku, D., Keane, L., Kamentz, D., Ritter, G., Duckworth, A. L., Urstein, R., Gomez, E. M., Markus, H. R., Cohen, G. L., & Dweck, C. S. (2016). Teaching a lay theory before college narrows achievement gaps at scale. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(24), E3341–E3348. https://doi.org/10.1073/pnas.1524360113

Zhao, S., Setoh, P., Storage, D., & Cimpian, A. (2022). The acquisition of the gender-brilliance stereotype: Age trajectory, relation to parents' stereotypes, and intersections with race/ethnicity. *Child Development*, *93*, e581–e597. https://doi.org/10.1111/cdev.13809

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Authors

Jamie M. Carroll is a sociologist who studies stratification, education, mental and physical health, political engagement, and adolescent development. Her work investigates the ways in which institutions stratify individual outcomes across the life course by empowering some and disengaging others. She is currently a Senior Research Fellow at the Education Research Alliance for New Orleans at Tulane University.

David S. Yeager is a developmental psychologist with expertise in the science of adolescent behavior change and in educational interventions. He is a William T. Grant Foundation scholar, where the focus of his award is on the intersection between psychological interventions and social contexts. He is the PI of the National Study of Learning Mindsets and a member of the Mindset Scholars Network Scientific Steering Committee. He is an Associate Professor in the Department of Psychology at the University of Texas at Austin.

Jenny Buontempo is the Senior Database Administrator and Lead Programmer for the Texas Behavioral Science and Policy Institute at the University of Texas at Austin. She ensures efficiency and timeliness in code/syntax archiving, data cleaning and validation, and other related documentation tasks. Prior to working on the TxBSPI, Jenny was the lead programmer for Sean Reardon's Stanford Education Data Archive.

Cameron Hecht, Ph.D., is an NSF postdoctoral research fellow at the University of Texas at Austin in the Population Research Center. He seeks to identify motivational dynamics that influence students' engagement and performance in academic settings, and to develop psychologically-informed interventions to promote equitable outcomes in these contexts.

Andrei Cimpian is a Professor in the Department of Psychology at New York University. His research spans developmental, cognitive, and social psychology. Among other topics, he investigates how children think about intellectual ability—what is it? who has it?—and how these beliefs shape children's aspirations.

Pratik Mhatre is the Scientific Director of TxBSPI and the Study Director for the NSLM Initiative. Dr. Mhatre received his Ph.D. in Urban and Regional Science from Texas A&M University and his Masters in Public

Policy from Georgia Institute of Technology. Dr. Mhatre is currently working on whether mindsets and college access/readiness initiatives affect academic outcomes and exploring impact of educator mindsets, school norms, and classroom climate on students' learning mindsets at the high school and college level.

Chandra Muller is a professor of sociology at the University of Texas. Her current research focuses on the long run effects of high school coursework on midlife work and financial security, health, and political participation at the intersections of gender, race and ethnicity, social class, disability status, and immigration status.

Robert Crosnoe is currently the Associate Dean of Liberal Arts and Rapoport Centennial Professor of Sociology at the University of Texas at Austin. His main research areas are human development, education, family, and health; specifically, the connections among children's, adolescents', and young adults' health, social development, and educational trajectories and how these connections contribute to societal inequalities (e.g., social class, immigration).