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When expectation isn't reality: Racial disparities in overestimation and STEM attrition among first-year students in college

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Abstract

Existing research indicates that racially minoritized students with similar academic preparation are less likely than their represented peers to persist in STEM, raising the question of factors that may contribute to racial disparities in STEM participation beyond academic preparation. We extend the current literature by first examining race-based differences in what students expect to receive and their actual grades in introductory STEM college courses, a phenomenon termed as overestimation. Then, we assess whether overestimation differentially influences STEM interest and persistence in college. Findings indicate that first-year STEM students tend to overestimate their performance in general, and the extent of overestimation is more pronounced among racially minoritized students. Subsequent analyses indicate that students who overestimate are more likely to switch out of STEM, net academic preparation. Results from regression models suggest that race-based differences in overestimation can be explained by pre-college academic and contextual factors, most notably the high school a student attended.

Keywords: STEM, calibration, higher education, regression analysis, survey analysis

When expectation isn't reality: Racial disparities in overestimation and STEM attrition among first-year students in college

As enhancing national diversity in STEM fields remains a priority, colleges are faced with the reality that many students, particularly those from underrepresented groups, leave STEM fields (National Academies of Sciences, Engineering, and Medicine, 2016). The lack of diversity in STEM fields is driven by STEM attrition: about a quarter of all college Science, Technology, Engineering, and Mathematics (STEM) entrants switch to a non-STEM major, and a greater proportion -- 30% of underrepresented-in-STEM racially minoritized students such as Black, Latinx, Pacific Islander, and Native Americans -- switch to a non-STEM major (Chen, & Soldner, 2013). Existing studies found that, even conditional on prior academic preparation, racially minoritized students are more likely to leave STEM fields than their White counterparts (Riegle-Crumb et al., 2019; Thompson, 2021). Research has explored various factors that may contribute to racial inequities in STEM persistence beyond individual academic preparation, such as course misalignment between high schools and colleges that disproportionately affect racially minoritized students' access to college-level courses (e.g., Park, Ngo, & Melguizo, 2020; Rodriguez, 2018), and experiences of stereotype threat that influence racially minoritized students' sense of belonging and engagement (Canning et al., 2019; McGee, 2018; 2020).

In addition, while academic preparation and grades in STEM introductory coursework correlate with subsequent STEM persistence, how individuals respond to their grades may depend on other factors such as their grade expectations and self-efficacy (e.g. Correll, 2004; Thompson, 2021; Tyson et al., 2007). For instance, expecting to perform well in a course but performing sub-optimally has been shown to hinder college students' academic progress (e.g., Bol & Hacker, 2001; Erlinger et al., 2008; Osterhage et al., 2019; Stinebrickner & Stinebrickner, 2012, 2014; Serra & DeMarree, 2016). Accordingly, student persistence may be more negatively impacted by a low grade when the gap between that grade and the one expected is wider. Yet, current studies have not directly examined whether misalignment between grade expectations and actual performance may indeed contribute to racial disparities in STEM participation.

This paper extends this literature by examining race-based differences in expected and actual grades in introductory STEM courses in college. Specifically, we leverage two waves of surveys administered at the beginning and at the end of introductory STEM courses at a large four-year university that collected information on what grade students expect to receive in STEM courses, documented what grades they actually received, and disaggregate these patterns by racial identification. We use the term racially minoritized to group together underrepresented-in-STEM racially minoritized students, but note that over 80% of this group in our study sample identify as Latinx, which reflects the broader community and our research setting.

Then, we examine whether such misalignment is related to loss of STEM interest -- often a process preceding STEM attrition (Cromley et al., 2016; Rosenzweig et al., 2020; Seymour & Hunter, 2019) -- and eventual STEM attrition. We focus on STEM introductory courses as these serve as the linchpin to upper-level STEM courses and are often the first impression students receive regarding a particular field of study (Gasiewski et al. 2012). In capturing misalignment between expected grades and actual grade, we focus on the extent to which students expect to perform well in a course but end up underperforming, a phenomenon we refer to as overestimation. We focus on overestimation as prior studies found that overestimating one's academic performance alters students' academic choices such as switching out of STEM fields into non-STEM fields (Stinebrickner & Stinebrickner, 2014). We add to this line of work by exploring possible racial gaps in overestimation, factors contributing to these gaps, and the extent to which these gaps may contribute to racial disparities in STEM persistence.

Specifically, our study is motivated by the following two main research questions:

1) *Do underrepresented-in-STEM racially minoritized students, defined as Black, Latinx, Pacific Islander, and Native Americans, overestimate their performance more than their represented peers in introductory STEM courses, and if so, to what extent can these gaps be explained by individual and contextual factors?*
2) *2) To what extent is overestimation related to the racial disparities in STEM interest and persistence?*

We construct measures of overestimation and link them to college academic outcomes using administrative data and student survey data collected from a large swath of gateway STEM courses at a public research university. We start by describing the raw racial disparities in overestimation patterns, and then examine the relationship between these disparities and various individual and contextual predictors both pre- and during college, including (i) prior academic achievement (e.g., high school GPA); (ii) non-academic measures at the beginning of college (e.g., survey measures of task value); contextual factors such as (iii) the high school a student attended and (iv) the peer composition of their initial college classes (e.g., the average achievement of students in the class). Our predictors are not exhaustive and notably exclude many relevant experiences in college (i.e., college academic experiences are also determined by instructor grading practices and biases and/or the racialized experiences in STEM departments). Nonetheless, by examining the relationship between various individual and contextual factors and race-based differences in expected and actual performance, our study will inform the design and implementation of collegiate programs and practices targeted to support racially minoritized students' transition from high school to college.

This study extends the literature on racial disparities in STEM persistence in at least three ways. First, by focusing on nearly 2,000 undergraduates taking introductory STEM courses at a large public institution that enrolls a significant proportion of racially minoritized students, our study is among the first to examine race-based differences in overestimation patterns and their association with STEM persistence. Knowing whether racially minoritized students overestimate their academic performance to a larger extent than their represented peers can help high school and college stakeholders address issues related to overestimation before students enter college STEM courses. Second, studies have established that prior academic achievement is a key predictor in overestimating one's abilities in college. We extend this line of work by offering a more comprehensive exploration of individual and contextual factors both pre and during college that may contribute to overestimation, notably the high school attended by a student. Finally, while there is a positive link between accurate assessment of one's abilities and course-level achievement (Osterhage et al., 2019), the link between misaligned expectations and long-term college outcomes has received far less attention. The survey studies conducted by Stinebrickner and Stinebrickner provide valuable insights into the relationship between beliefs about one's academic ability and college dropout (2012) and major selection (2014). We build on their studies by including measures of short-term interest in STEM fields, as well as longer-term academic outcomes, such as eventual STEM degree attainment six years after initial college enrollment.

The structure of the paper is as follows. We first present a theoretical discussion related to overestimation and then review relevant literature on factors that may contribute to overestimation and why overestimation might lead to STEM attrition. Next, we discuss the data structure and hone in on our analytical sample. We discuss our estimation strategy, proceed with the main results, and conclude with a discussion of our findings.

Theoretical Grounding and Relevant Literature

The scope of this study on overestimation is broad. Although our primary aim is to understand whether STEM attrition is a function of overestimation, we also intend to offer practical implications by investigating how students' likelihood to overestimate emerges from differences in their developmental context (e.g., prior achievement, values) and social contexts (e.g., high school and college classmates). Eccles and colleagues' Situated Expectancy-Value Theory (SEVT) of motivation (1983, 2020) is a widely used theory within educational psychology that emphasizes the importance of students' expectancies of success ("Can I do it?") and value beliefs ("Do I want to do it?") when understanding their motivation for academic choices such as selecting/switching college majors. Appropriately for this study, SEVT has also evolved to acknowledge how social, developmental, and cultural contexts influence students' interpretation of their experiences and form expectations of success. The SEVT can be integrated with the extant literature on overestimation to systematically explore the ways in which sociocultural contexts and the identities of the student influences and are influenced by the phenomenon of overestimation.

Conceptually, overestimation implies a mismatch between students' expectations and actual performance in college. Studies on the phenomenon of overestimation converge to highlight the importance of information in making a more accurate self-assessment (Bol & Hacker, 2012). Yet, students who are the first in their family to attend college, low-income, or from racially minoritized background are less likely to be given adequate information about what to expect when they enter college (Rodriguez, 2018), highlighting links between SEVT's cultural milieu and expectation of success. Comparing high school students' estimated college costs and the actual cost of college, Nienhausser and Oshio (2017) found that Black and Hispanic students were more likely to overestimate the cost of college than White students (Nienhusser & Oshio, 2017). Similarly, students who are the first in their family to attend college, while drawing from rich cultural and familial knowledge and college-going values (Luedke, 2020), tend to have less access to individuals with first-hand knowledge of college expectations compared to students with college-educated parents (Tierney & Duncheon, 2015). Due to being less familiar with college expectations, racially minoritized students or first-generation college students may overestimate their performance during the first term more so than represented students. In a similar vein, these students tend to be concentrated in under-resourced high schools with, for example, fewer opportunities to obtain college counseling (McDonough, 1997, 2005), suggesting that overestimation may be more prevalent in under-resourced schools.

Aside from the general recognition that racially minoritized students tend to receive less information about what to expect in college, students' race/ethnicity intersects with several factors that literature suggests is linked to overestimating in college. Below, we review what the literature suggests are factors that may contribute to overestimation, and present theoretically grounded arguments for why there may be an association between overestimation and differential patterns of STEM attrition by race.

Factors Contributing to Overestimation

A number of studies have explored individual factors related to a student's possibility of overestimating their ability to perform well in a course, including: (i) prior academic achievement, such as high school GPA; (ii) non-academic factors, such as utility value, and pre-college and initial college contextual considerations such as (iii) the high school context as well as (iv) the average characteristics of their initial course in college. Below we discuss each category.

Prior Achievement

Eccles' and colleagues' SEVT emphasizes the link between previous achievement related experiences and expectations of success across time. A key mediator of that process is students' interpretation of those experiences, which shapes future expectations of success. In science classrooms, the lowest-performing students are consistently those who are most likely to overestimate their performance (Dang et al., 2018; Jensen & Moore, 2008; Ziegler & Montplaisir, 2014). The strong association documented in the existing literature between academic achievement and overestimation is largely explained by the "Dunning-Kruger effect," which is that people who suffer the most from gaps in their knowledge are the least likely to recognize those limitations and calibrate accordingly (Dunning, 2011).[1] The same skills students use to achieve in school are also important for their ability to accurately interpret how well they will be able to perform in the future (Kruger & Dunning, 1999). Therefore, academically underprepared students are more likely to overestimate their abilities (Erlinger et al., 2008), a phenomenon that has been observed across a variety of settings, including in introductory STEM courses (Osterhage et al., 2019).

Non-Academic Measures

[1] Some critics (Krueger & Muller 2002) have argued that this effect could be due to statistical artifact (e.g., regression to the mean). Erlinger and colleagues (2008) addresses this in five studies and found that bottom performers dramatically overestimated their performance even after accounting for unreliability of performance measures.

In contrast, SEVT (Eccles, 2020) suggests that students who are especially excited about upcoming coursework may actually inflate their expectations of success. Expectancies of success in a course and perceived value of that course are stipulated as the most proximal predictors of motivation. For example, students may find a course has more value due to their perceptions of its utility value (e.g., tasks that are useful for one's goals) or their interest in it. Because expectancies and values have been shown to positively influence each other, it is possible that those who see greater value in a task are more likely to have higher performance expectations, independent of their ability levels (Wigfield et al., 2015). Moreover, theory indicates that racially minoritized students who perceive especially high expectancies and value for STEM subjects tend to sustain motivation despite structural academic barriers during high school (Fuligni et al., 2005; Graham, 1994; Graham & Taylor, 2002; Wigfield et al., 2012). Indeed, a recent study of incoming engineering students showed that after controlling for prior achievement, racially minoritized students had higher value for engineering as they entered college, and as theory would suggest, this was complemented by higher expectancies for success (Robinson et al., 2019).

The High School and Initial College Classroom Context

In addition to prior achievement and values, students' perceptions of abilities and college expectations are also shaped by the social context. Researchers using SEVT to guide their work have noted for decades that ability beliefs are largely determined through a subjective process by which students compare themselves to those around them (Bong & Clark, 2010; Marsh & Parker, 1984), making the average ability level of a student's high school classmates critical for determining their ability beliefs as they enter college. As a result, students from under-resourced high schools might be especially likely to overestimate due to the "big-fish-little-pond" effect, which highlights the possibility that students who achieve at the same objective level can have different perceptions of their academic abilities if they are comparing themselves to peers with different achievement levels (Elsner & Isphording, 2017; Marsh, 1987). For instance, academically mediocre students may perceive themselves as having high ability if they are surrounded by lower-performing peers. Conversely, a high-achieving student is likely to perceive themself as having low ability if they are surrounded by superstar peers with even higher achievement levels.

Once students arrive at college, their grades may depend on how they perform relative to their classmates, especially in gateway courses where grades are often assigned “on a curve.” If students from the highest and lowest performing high schools find themselves in those same college classrooms at competitive universities, new undergraduate students from the lowest performing high schools would run into higher risk of overestimating their performance to the extent that they have not been prepared to recognize how much the average ability level of their college classmates exceeds that of their high school classmates. Given systemic inequities to accessing adequate college-related information along racial lines, we might expect racially minoritized students to be especially likely to experience these barriers. Although the distribution of GPA and SAT scores are not as wide in competitive universities relative to open-access institutions (Geiser & Santelices, 2007), these distributions belie the much wider array of high school and environmental contexts that shape students’ perceptions of their academic abilities and what to expect in college. The achievement levels of classmates in students’ high school context and initial college classroom context are therefore likely to play their respective roles in shaping students’ predictions about their performance.

Overestimation and STEM outcomes

Students' beliefs and expectations for success play a major role in motivation and subsequent behavior such as persistence. Specifically, students' beliefs about the likelihood of performing well on a task (i.e., "I can do this") is a major determinant of goal setting, activity choice, willingness to expend effort, and persistence (Bandura, 1977). Although SEVT shows that higher expectation for success is generally thought to be a positive self-belief that helps students confidently choose and persist (Eccles & Wigfield, 2020), overestimation of one's ability is linked to academic underperformance and attrition. Within a given class, the ability to accurately judge what one knows and does not know is associated with greater metacognitive skills, effective study strategies, and better course performance (Bol & Hacker, 2001; Garavalia & Gredler, 2002; Osterhage, Usher, Douin, & Bailey, 2019; Zimmerman, 2008). This is because an accurate understanding of one's current abilities allows students to self-regulate their study behavior more wisely to gain the knowledge required to succeed (Kornell & Bjork, 2009; Hacker, Bol, & Bahbahani, 2008). Conversely, students who overestimate their ability may underinvest during the learning process, such as stopping short before achieving mastery (Dunlosky & Thiede, 2013; van Loon et al., 2013). Overestimation can therefore play a role in lowering students' performance throughout a course (Osterhage et al., 2019).

The only studies to our knowledge that examined the relationship between overestimation and longer-term academic outcomes are two studies conducted by Stinebrickner & Stinebrickner (2012, 2014). The authors administered a survey to two cohorts of first-year students before they started the school year and gathered data on students' confidence and expected performance in their major, expected GPA, and dropout probability. They examined whether updating one's beliefs is associated with dropping out of college (Stinebrickner & Stinebrickner, 2012) and switching out of science majors (Stinebrickner & Stinebrickner, 2014). These studies found that students who were substantially overoptimistic about their grade performance were more likely to leave college. Moreover, Stinebrickner and Stinebrickner (2012) showed that students who left school in the first three semesters were by far the most over optimistic about future grade performance and, subsequently, had the largest downward revisions to beliefs. In addition, Stinebrickner and Stinebrickner (2014) found that being overoptimistic about grade performance in science contributed to switching to a non-STEM major. We extend this work by exploring whether racially minoritized students show different patterns of overestimation, and whether overestimation contributes to racial disparities in STEM attrition.

Data and Sample

Study Context

This study was conducted at a large, selective, public research university in California. In fall 2013, 44% of first-year undergraduates entered as STEM majors out of 23,530 undergraduate enrollees at this institution. Students categorized as STEM entrants included those majoring in engineering, computer information sciences, physical sciences, and life sciences majors (see Appendix A.1 for a full list of STEM majors). Of the students who matriculated at this institution in fall 2013, 25% were identified as Latinx, Black, American Indian, or Pacific Islander whereas 65% were either White or Asian.[2] In this paper, we grouped diverse Asian subpopulations together but recognize that this level of grouping masks the nuance of attainment. Specifically, Vietnamese, Cambodians, Hmong, and Laotians in addition to Pacific Islanders tend to be underrepresented in STEM fields (Shivaram, 2021). We include East Asians in the

[2] Asians are overrepresented in our study sample but we do not disaggregate Asians into Asian sub-categories as well as distinguish this group from White students as the focus of the paper is not on represented students.

represented group category given their overrepresentation in STEM majors but acknowledge that Asians broadly conceived are racially minoritized in various societal contexts. This institution enrolled similar percentages of racially minoritized students relative to public research universities across California in fall 2013 (see Table 1).

Students at this institution tend to have strong academic backgrounds. According to a recent analysis produced by the institution, the average admitted students have a high school GPA of 3.8 and above and 83 percent of students graduate with a Bachelor's degree in six years. Yet, this institution still struggles to retain students in STEM fields, with non-trivial gaps in STEM graduation between underrepresented and represented groups. Among the racially minoritized students who entered as a STEM major in 2013, 74% completed a degree in STEM in six years, compared to 85% among represented students, underscoring the challenge in retaining students from traditionally underrepresented groups in STEM fields.

Data and Sample

In fall 2013 and winter 2014, a team of researchers surveyed first-year undergraduates in a large swath of introductory STEM courses at the beginning and at the end of the quarter. The survey was administered as part of a larger study that involved collecting classroom observation data and examining instructional practices in introductory STEM courses (Reimer, Schenke, Nguyen, O'Dowd, Domina, & Warschauer, 2016). The goal of the survey was to collect information on students' expectations of course performance and various non-academic factors, such as interest in the subject area (e.g., pre- and post-measures were included based on student responses to the survey administered at beginning and at the end of the term).[3]

[3] See Appendix A.2 for specific survey measures.

As existing research indicates that overestimation is particularly prevalent among first-year students (e.g. Gross & Latham, 2011; Osterhage et al., 2019; Stinebrickner & Stinebrickner, 2012, 2014), we focus on students who matriculated for the first time at this university during fall 2013. 71 sections across 33 courses in Biology, Chemistry, Engineering and Computer Science, Physics, and Math were surveyed for the study.[4] Survey responses were linked to students' administrative records to create a comprehensive datafile that includes students' perceptions of ability and interest, measures of overestimation, course performance, and their demographic profile.

A total of 3,774 unique first-year students participated in the survey during fall 2013, which yielded 5,864 student-by-section observations.[5] From the 3,774 unique student observations, we removed students who did not respond to our key overestimation survey measure (n=899), who did not declare STEM as their major (n=688), and who were transfer students (n=142), which resulted in 2,045 STEM students. The majority of these students tended to demonstrate consistent patterns in either overestimating or underestimating their performance across STEM introductory coursework. Yet, 214 students (about 10% of the sample) showed a mix of overestimation and underestimation across STEM courses (i.e. overestimated in one course and underestimated in another). These students were removed from our analyses due to the difficulty of classifying them in the overestimation or underestimation sample.
Therefore, students who did not clearly fall into either group were removed to improve the validity of our conclusions about overestimation or underestimation. Less than 10% of the

[4] We use the term "section" or "class" to refer to a course being offered at a specific time and taught by a specific instructor (e.g., Biology 93 offered on Monday and Wednesday at 9 a.m. taught by Professor A).
[5] The survey response rate by class ranged from 31% to 97%. In most classes, students were incentivized to take the survey in the forms of extra credit in the class.

sample (n=188) precisely estimate their performance. Those who precisely estimated their course performance were included in the underestimation sample since literature is less clear on whether students who underestimated and precisely estimated their performance would differ from one another. In our setting, those who underestimated or precisely estimated performed higher than those who overestimated, indicating that precise estimators, on average, may be more similar to underestimators than overestimators in the context of academic performance. Our final analytical sample includes 1,831 unique non-transfer, STEM students whose entry term was fall 2013 with valid overestimation survey responses. Among the 1,831 unique students, 1355 students (74%) are included in the overestimation sample.[6]

< Insert Table 1>

As shown in Table 1, compared with average first-year students who entered a public four-year institution in California, a larger proportion of students in our focal sample are identified as Asian (62% versus 37%). In addition, fewer students are categorized as low-income than students in the state (39% versus 42%). Whereas about 44% of first-year students enter the institution of the current study with a STEM major, all of the students in our focal sample, by definition, are STEM entrants. Despite these differences, Table 1 shows that our focal sample consists of a similar proportion of racially minoritized students and women relative to the institution and the state. Given that there are significant representations of underrepresented

[6] Among the 1,831 students, 69% took the survey more than once depending on the number of STEM courses a student took that was within the purview of our sample. For these students, we obtained course-specific overestimation scores and averaged them. For example, if a student took an introductory biology course and an introductory chemistry course in fall 2013 and participated in surveys in both courses, we calculated the gap between their actual and expected grades across both courses and then averaged between them. As mentioned previously, students who flip-flopped (i.e. overestimated in one course but underestimated in another course) were removed from our analyses. Therefore, students in our sample are those who consistently overestimated or were consistently accurate/underestimated their course performance.

students in our sample, our survey data are well suited to examine how the extent of overestimation varies by race.

Key Measures

Overestimation. The pre-course survey, administered during the first two weeks of the term, asks students "*what grade do you expect to receive in this course?*". Using this survey measure, we operationalize overestimation as the gap between a student's expected score she will receive in her STEM gateway course and her actual grade. By benchmarking students' responses with actual grades, we identify the extent to which students miscalibrated their academic performance. Specifically, we first assign numeric values to students' anticipated and actual grades using a scale of zero through 12 with a zero representing an "F" and a 12 representing an "A+". We then subtract a student's actual grade from her expected grade. For example, a student who expected to receive an A in the course (11) but received a B- (7) would receive an overestimation score of 4. Therefore, a positive value indicates that a student overestimated her performance, with larger values indicating greater extent of overestimation. In contrast, a value ranging from zero to negative indicates that the student was either accurate in her predictions or underestimated her performance.

Similar to how Erlinger et al. (2008), Osterhage et al. (2019), and Stinebrickner and Stinebrickner (2012)[7] examined overestimation, we use a continuous measure to assess the extent of overestimation, and this measure serves as the main variable in all of our analyses. However, there are slight nuances in how these authors operationalized overestimation compared

[7] Stinebrickner & Stinebrickner (2012) subtracted expected GPA from actual GPA. Then, to examine the relationship between overestimation on dropout, they include students' beliefs about grade performance as an independent variable controlling for overall GPA. In Stinebrickner & Stinebrickner (2014), they take on a different approach in which they examine initial and expected GPA in science and non-science majors controlling for overall GPA to tease out different academic expectations associated with majoring in science and non-science fields.

to this study. Similar to our study, these authors subtracted students' predicted performance from their actual performance to determine the extent to which students overestimated their ability. Different from our study, some studies benchmarked overestimation with college GPA (Stinebrickner & Stinebrickner, 2012), while others benchmarked overestimation with exam performance (Osterhage et al., 2019). Moreover, some authors lumped all students together to examine miscalibration more broadly rather than dividing those who miscalibrated as overestimators or accurate/underestimators (Osterhage et al., 2019). Yet, as evidence points to the prevalence and consequence of overestimation, we distinguish it from accurate prediction or underestimation.

< Insert Figure 1>

Figure 1 examines the distribution of the gap between expected and actual grades and whether the distribution differs between racially minoritized students and represented students. The figure suggests that both racially minoritized and represented students expect to receive A's or B's in the course with no student in both groups expecting to receive an F. However, racially minoritized students end up overestimating more as their actual grades in the course are more widely distributed than represented students.

STEM Outcome Measures. We examine two STEM-related outcome variables: STEM interest measured at the end of the course and STEM degree attainment after six years of initial college enrollment. We model STEM interest as a composite score that captures students' interest in the subject matter of the course. Specifically, the STEM interest survey items are: *"I find many topics in this course to be interesting"*; *"Solving problems in this class is interesting for me"*, and *"I find this class intellectually stimulating"*.

We identify students' initial major at the time of admittance (fall 2013) and their final major at the time of graduation to create an indicator of STEM attrition.[8] The last term observed in the dataset is spring 2019, thus allowing us to track students for six years. We define STEM attrition as students who initially enrolled in a STEM major at the start of college and graduated with a non-STEM major after the first term. We observe the graduation outcomes of all students in our analytical sample and thus are able to capture students' major switching patterns.

Key Covariates**.** We include race, gender, socioeconomic status as measures of demographic characteristics and high school GPA and SAT scores as measures of prior achievement during high school. Non-academic measures include pre-survey responses administered at the beginning of the term. These pre-survey measures were used to create three composite variables of self-efficacy, task value, and utility. We obtained institutional data of all students in the course irrespective of whether they answered the survey and constructed class level means to create class composition measures such as the average incoming achievement level of the class. Finally, we also merged in variables from the Common Core of Data to obtain high school characteristics.

Estimation Strategy

Our first research question asks whether greater prevalence of overestimation among racially minoritized relative to represented students is evident once we include covariates that literature suggests is associated with the extent of overestimation. Specifically, we examine the

[8] Students whose initial major is "undeclared" but who are admitted specifically to the university's STEM schools (e.g., School of Physical Sciences) are included as part of the STEM student sample.

relationships between four categories of covariates and the extent of overestimation using an ordinary least squares regression, which is formally written below in Equation (1),

$$Overestimation_{ics} = \beta_0 + \beta_1(RM_i) + \chi_i\beta + \chi_c\varphi + \gamma_s + \varepsilon_{ics} \quad (1)$$

where $Overestimation_{ics}$ is a continuous indicator that measures the gap between the actual and predicted grades for student *i* who graduated from high school *s* and took the survey in class *c*. We include a binary variable indicating racially minoritized (RM) students or represented students as the main predictor. χ_i represents a vector of other demographic characteristics, prior achievement, and non-academic factors and χ_c indicates a vector of class composition measures to tease out the unique variation in overestimation patterns across courses with comparable class composition. β and φ refer to the unstandardized coefficients associated with each predictor, with higher positive values indicating greater gap in what students, on average, expect to receive and their actual grades. Finally, we include high school fixed effects to compare students who graduated from the same high school (γ_s). Equation (1) estimates whether racially minoritized students are more likely to overestimate compared to represented students.

We then model equation 2 to estimate the association between the extent of overestimation and an individual's short- and long-run STEM outcomes among the racially minoritized and non-racially minoritized student sample:

$$y_{ic} = \beta_0 + \beta_1(Overestimation_i) + \chi_i\beta + \chi_c\varphi + \varepsilon_{ics} \quad (2)$$

where y_{ic} indicates STEM interest and six-year STEM degree attainment for student *i* in class *c*. $Overestimation_i$ is a measure of the degree to which students' predicted score is greater than their actual score. We include the same covariates as specified in equation (1), but exclude high school fixed effects as the relationship between overestimation in college and STEM interest and long-run college outcomes are determined by students' college experiences. In other words, our first research question places the focus largely on expectations formed prior to college while our second research question examines factors associated with students' experience while in college.

Results

Factors Associated with Overestimation

Table 2 columns 1 through 5 examines the five categories that may be associated with overestimation. Column 1 includes four demographic characteristics as specified in equation (1) and therefore shows the raw percentage point difference on the overestimation measure between racially minoritized and represented students. The estimates indicate that racially minoritized students relative to represented students were more likely to overestimate by a grade separation of one in introductory STEM courses ($p < 0.001$). This average gap is equivalent to expecting to receive a B+ but actually receiving a B in the course.

< Insert Table 2 here >

We then sequentially include different sets of covariates in columns 2 through 5 to examine the extent to which the demographic gaps in overestimation shown in column 1 can be explained due to the inclusion of four categories of individual and contextual factors, namely prior achievement, non-academic factors, college class composition, and the high school a student attended. If academic preparation is correlated with both overestimation and subgroup identification, the demographic gaps in the extent of overestimation may attenuate once we account for prior academic preparation. Indeed, estimates shown in column 2 indicate that students' prior academic preparation, including SAT math and verbal scores and high school GPA strongly predict students' likelihood of overestimating their course performance. Specifically, students with one standard deviation higher SAT math score are associated with a decrease in their overestimation score by about one which is equivalent to being a third of a grade more accurate ($\beta = -1.057;\ p < 0.001$). Similarly, students with a standard deviation higher high school GPA were less likely to overestimate ($\beta = -0.466;\ p < 0.001$). Additionally, once we account for prior academic preparation the overestimation gap between racially minoritized and represented students becomes attenuated by more than half from 0.908 to 0.424 and statistically insignificant at the 0.05 level.

Column 3 further includes pre-course levels of self-efficacy, utility, and interest in the course, and column 4 adds measures of the class composition. The estimates indicate that students who had higher perceived course utility were less accurate in their grade predictions than students with lower perceived course utility while higher measures of interest are associated with decreased level of overestimation. As for indicators of class composition, students in classrooms with higher achieving peers, as measured by average SAT math scores, were more likely to overestimate their course performance. It is important to note that after we include non-academic measures and measures of class composition, the racially minoritized coefficient is still positive but no longer statistically significant. In column 5, we further include high school fixed effects to retrieve within high school estimates, and the estimated gaps in overestimation between racially minoritized and represented students were further attenuated from 0.36 to 0.08. In other words, race-based differences in overestimation patterns are explained away by other factors such as the high school attended and prior academic achievement.

Moving from columns 1 through 5, we also observe a gradual increase in the proportion of overall variation in overestimation explained. From a model that included only demographic characteristics, we find that including high school preparation measures substantially increased the R^2 from 0.05 to 0.16, indicating that prior academic achievement explains a substantial amount of the overall variation in overestimation. Adding non-academic indicators and class composition measures increase the overall variation explained to 19%. Among all the different covariates, adding in high school fixed effects increases the overall variation most substantially, from 19% to 55%, indicating that where students attended as their high school is one of the strongest predictors of the variation in overestimation.

In view of the strong correlations between the high school attended and overestimation, we further focus on high school characteristics that may be associated with an individual's overestimation score (Table 3). As theory and literature suggest, equally-able students have different perceptions of their academic abilities depending on the achievement levels of their peers (Elsner & Isphording, 2017; Marsh, 1987). For example, students in lower-performing high schools may be more likely to overestimate their performance than their peers in higher-achieving high schools as a result of the differential peer ability composition. We explore this possibility by focusing on a subset of students in our sample who graduated from a California high school. Until 2013, high schools in California were ranked from 1 to 10 using the Academic Performance Index (API), a ranking measure of high school quality using the California standardized testing results with one being the lowest ranking and 10 being the highest ranking.[9] High-achieving high schools are schools that scored a 9 or a 10, mid-range schools scored

[9] The most recent year in which high schools were ranked using standardized tests was in 2013. The California Department of Education launched a new high school accountability system based on multiple measures after 2013.

between 3 through 8, and low-achieving schools scored a 1 or a 2. There are limitations to identifying high-achieving high schools based on their API score such as gaming the system or narrowly defining achievement using only standardized test score performance (see Polikoff & McEachin, 2013, for review). As such, we cautiously interpret these findings as a proxy for school competitiveness using standardized tests. This analysis is limited to non-international students who graduated from a high school in California, which is 80% of the overestimation sample (n=1,091).

< insert Table 3 >

Table 3 shows different overestimation patterns depending on the high school. Because the Academic Performance Index is correlated with socio-economic characteristics of the schools (Polikoff & McEachin, 2013), we include whether the high school received federal funds (i.e., Title I status) into the model to control for variations in school resources. Furthermore, we control for the school locale (e.g., urban, suburban, or rural) as research suggests the location is a predictor of school quality (Lavalley, 2018).[10]

We find suggestive evidence that students who may have been “big fishes” in their high school were more likely to overestimate their course performance relative to students who may have been “small fishes” in their high school conditional on observable school resources. Specifically, relative to students from high schools where many excelled on the California standardized tests (i.e., API score of 9 or 10), students from schools where many underperformed on the standardized tests (i.e., API score of 1 or 2) were more likely to overestimate their course performance in college (see Table 3, column 1). Students from schools with the lowest API score

[10] High school characteristics were obtained from the Common Core of Data.

have an overestimation gap that is 0.64 units higher than students from schools with the highest API score even after accounting for students' own characteristics, the composition of their peers in the introductory STEM course, and measure of high school characteristics such as school resources and locale. Thus, overestimators tend to be concentrated in the lowest-achieving high schools.

< Insert Table 4 >

The analyses so far focus on race-based overestimation patterns in students' entry-level coursework. The SEVT and prior literature suggests that the phenomenon of overestimation may change over time and is malleable. For example, Osterhage et al. (2019) found that students were better able to calibrate their academic performance as instructors provided feedback throughout the term. We also explore this possibility empirically using our data by focusing on a subset of students in our analytical sample (n=626) who enrolled in another STEM course in the subsequent term (winter 2014) and participated in our pre- and post-course surveys. At this point, students already spent some time in college and may become more attuned to the collegiate environment and course requirements, as well as their own academic capacity based on information received through their initial experiences in college. Raw average differences shown in Table 4 indicate that although students still tend to overestimate their course performance, the average gap in students' expected and actual grades narrowed from approximately 4 points (e.g., expecting an A and receiving a B-) during the first term to 3 points (e.g., expecting an A and receiving a B) in the subsequent term. Moreover, racially minoritized students experienced noticeable improvement in accurately predicting their course performance.

Overestimation and STEM outcomes

Students make behavioral choices that align with their outcome expectations (Eccles et al., 1983; Lent et al., 1994). In addition, they tend to rationalize that there is greater value in the tasks that they are good at (Wigfield et al., 2015). Therefore, students who expected to do well in STEM courses may lose interest in the subject once they realize their actual performance in the course is lower than what they anticipated. In table 5, we investigate the relationship between overestimation and STEM interest at the end of the term accounting for their initial level of STEM interest at the beginning of the term. Column 1 indicates a significant association between overestimation and the loss of students' interest in STEM at the end of the term, and columns 2 and 3 examine this relationship by subpopulations. We find that the negative association is concentrated among represented students. However, Wald test for whether the linear combination of the coefficients on overestimation by race equal zero indicates non-significant differences.

< Insert Table 5 >

Next, Table 6 estimates the relationship between overestimation and STEM attrition within six years of enrollment. Column 1 examines STEM attrition of the full sample of students, column 2 examines this relationship among a subsample of racially minoritized students, and column 3 examines STEM attrition among represented students. All models include the full set of covariates listed in Table 5. As shown in Table 6, overestimation is a statistically significant predictor of STEM attrition, and this pattern is consistent across all subsample populations. Focusing on column 1, a one-point increase in students' overestimation score among overestimators (for example, expecting to receive a B+ but earning a B) is associated with a six percentage point increase in overall STEM attrition. This pattern remains consistent across subsamples; however, a subsequent joint test indicates that the overestimation coefficients across models are not significantly different. The results therefore indicate that higher overestimation score is associated with greater likelihood to leave STEM fields for students of all races.

< Insert Table 6 here >

Limitations and Future Research

While we have course-level measures of overestimation nested within students, the outcome of STEM attrition was measured at the student-level; therefore, operationalized overestimation as the extent of overestimation at the student-level. Future studies, however, may consider taking into account between-class variation in overestimation and explore how the relationship between overestimation and STEM persistence may vary by the characteristics of the specific course. For example, the association between overestimation and STEM attrition may be more pronounced when examining core courses for a major than for elective courses.

Relatedly, our study grouped STEM courses together as under one category due to small sample size but students taking Math courses may overestimate to a larger degree than students taking a Biology course or vice versa. In Appendix Table A.3, we start to unpack the nuances within STEM disciplines and find that students in Math courses overestimate to a greater degree than students in Physics. One hypothesis for STEM subject-specific differences may be due to systematic underperformance among students matriculating in Math courses. These patterns warrant attention in future research.

Second, an area worth closer examination is college contextual factors that may shape students' perceptions of their academic abilities. Many factors could contribute to students' overestimation beyond the set of variables we have access to, such as the culture of the STEM environment (McGee, 2020), student supports and services (Kitchen et al., 2018) and instructional approaches (Park et al., 2021). In particular, instructors of undergraduate introductory STEM courses frequently incorporate achievement relative to peers in order to create variance among students along a normal distribution. Students unaware that grades may be determined by the performance of their peers may not consider their ability relative to their peers when judging their own expectancy of success. As a result, their performance in the grade may be due to a curved grading system or systemic biases in grading and teaching that disadvantage underrepresented students. Therefore, it is critical that future research expand on what we examined to study the college classroom context that contributes to the phenomenon of overestimation. Nevertheless, we note that our non-exhaustive list of student and contextual factors that predict the extent of overestimation provides an overview of this phenomenon and also reveals important patterns that deserve policy attention.

Third, we aggregated different underrepresented-in-STEM racially minoritized students into one racially minoritized category which masks the unique experiences of different racial groups. We re-do our analysis focusing on the Latinx subsample as over 80% of the racially minoritized students in our study identify as Latinx. These results, in Appendix Tables A.4 through A.6, show that the direction and magnitude of the results are similar as the main results. Due to the small sample size, we are unable to conduct the same regression-based analysis for the remaining racially minoritized students. Instead, we present raw differences between predicted grade and actual grade by race in Appendix Table A.7. The results indicate that all racially minoritized students overestimate in similar magnitude relative to represented students. Future inquiry that identifies more systematically the overestimation patterns and STEM outcomes across different racial groups is warranted.

Implications and Conclusion

As enhancing national diversity in STEM fields remains a priority (National Academies of Sciences, Engineering, and Medicine, 2016), it is necessary that researchers examine possible factors that contribute to racial disparities in STEM attrition. Existing research indicates that racially minoritized students with similar academic preparation are less likely than their represented peers to persist in STEM (Riegle-Crumb et al., 2019), underscoring the need to examine factors that may contribute to racial disparities in STEM participation beyond academic preparation. We extend the current literature by examining race-based differences in overestimation patterns in introductory STEM courses, and whether the misalignment between expected and actual grades are associated with STEM interest and persistence. We find that the extent of overestimation, measured as the gap in expected and actual grades in a course, is larger among racially minoritized STEM students but the gap is largely attributable to prior achievement and high school attended. Furthermore, we find suggestive evidence that STEM students who overestimated were more likely to leave STEM fields in the long-run. Specifically, STEM students who transitioned from high schools with low-achieving peers on to a competitive postsecondary institution were subject to a greater extent of overestimation, aligning with prior literature that ability beliefs are often constructed by comparing own performance with salient peers (Eccles, 1983; Elsner & Isphording, 2017; Marsh & Parker, 1984). Indeed, the SEVT model suggests that students will make sense of why their performance did not live up to their expectations by attributing the inconsistency with "this is not for me."

Considering that racially minoritized students are more likely to be concentrated in lower-performing schools, the strong association between the high school a student attended and the extent of overestimation in college is troubling from a racial equity perspective. Yet, the fact that students experience improvement in accurately predicting their performance after initial term in STEM fields reinforces the iterative nature of achievement-related expectations and bolsters the need for interventions and institutional resources to help racially minoritized students through proactive advising and support systems. High school counselors and teachers serve as an important source of college information for students, and especially so for racially minoritized students. Our study points to the need for proactive outreach among high school advisors and teachers to better inform students of both college-going opportunities and college academic expectations. We explicitly note that the advice must not be framed in a deficit perspective and should be crafted within a dialogue of care and support. For instance, outreach and discussion regarding college academic expectations can center around acknowledging the challenges of college-level courses and the need for increased level of effort by the student in college, while also framed to specify that all students face difficulties during their first year and that students should not shy away from reaching out for additional support. In fact, social-psychology literature has demonstrated that short framing interventions prior to college that target students' beliefs and feelings about college academic expectations can lead to substantial benefits for minoritized students by portraying that academic struggles are a normal part of the college experience, and that challenges can be embraced as important opportunities for growth rather than signs that students do not belong (Yeager et al., 2016).

Colleges can share in the responsibility of helping students develop accurate expectations of success by offering various programming before official coursework. Summer bridge programs are an example, typically offered during the summer before college, that provide support for students with unequal prior educational opportunities to better acclimate students to college expectations (Kitchen, Sadler, & Sonnert, 2018). Colleges may want to incorporate discussions on academic expectations and share ways to become successful in STEM coursework through such programs.

In addition, there are a number of ways instructors may better guide students toward more informed judgements about their capabilities and preparedness. One of the key ways to help orient first-year STEM students form accurate college expectations is to provide students with feedback early in the term. For example, instructors may administer formative assessments such as low-stakes quizzes early in the course so that students can update their ability beliefs and adjust their study behaviors in time. Another way instructors can support students in calibrating their academic beliefs is to increase their meta-cognitive knowledge and regulation. Instructors can provide evidence of the likelihood that they are overestimating and offer explicit ways that students can improve their understanding of how prepared they are for exams (e.g., Osterhage et al., 2019). In addition, instructors may also clarify steps necessary for successful learning in the course explicitly and intentionally throughout the term to help students adapt to the college environment.

Research has established that students with a better assessment of their abilities are more likely to exhibit learning strategies and behaviors conducive to academic success (Hattie, 2013). It is therefore important to determine whether incoming STEM students overestimate their academic abilities and whether this phenomenon affects their persistence. Collaboratively and iteratively setting students' expectations about college academic rigor is one of the ways to retain diverse STEM talent.

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Table 1

Sample Generalizability

	All first-year CA students		All first-year students at this institution		Focal students		
	M or %	**count**	**M or %**	**count**	**M or %**	**SD**	**count**
Racially Minoritized	26%	188,088	25%	23,530	23%	(0.42)	1831
White	26%	188,088	17%	23,530	13%	(0.33)	1831
Asian	37%	188,088	47%	23,530	62%	(0.49)	1831
Other	11%	188,088	11%	23,530	2%	(0.15)	1831
Women	52%	188,088	54%	23,530	51%	(0.50)	1831
Low-Income	42%	188,088	45%	23,530	39%	(0.49)	1831
HS GPA (Weighted)					3.96	(0.21)	1831
SAT Math					637.02	(80.66)	1830
SAT Verbal					567.90	(89.34)	1830
Entered as a STEM Major	42%	188,088	44%	23,530	100%	(0.00)	1831

Note. The column "All first-year CA students" indicate all undergraduates who first entered one of the University of California schools in fall 2013. The "column All first-year students at this institution" indicate those who entered this institution in fall 2013. Focal students are students who took introductory STEM courses at this institution, were given the opportunity to take the survey in fall 2013, indicated STEM as their major, and are non-transfer students with valid overestimation survey measure and course grades. Racially minoritized students are students who identify as Black, Latinx, Pacific Islander, or Native American.

Table 2

Predictors of Overestimation

	Demographics (1)	Prior Achievement (2)	Non-Academic (3)	Class Composition (4)	High School Fixed Effects (5)
Racially Minoritized	0.908***	0.424	0.446*	0.361	0.084
	(0.229)	(0.220)	(0.224)	(0.220)	(0.345)
First Generation College Student	0.355*	0.065	0.088	0.119	0.098
	(0.144)	(0.142)	(0.142)	(0.141)	(0.222)
Low Income	0.095	-0.091	-0.093	-0.110	-0.066
	(0.136)	(0.133)	(0.133)	(0.132)	(0.214)
Women	0.272*	0.028	0.059	0.142	0.295
	(0.124)	(0.122)	(0.125)	(0.133)	(0.207)
Asian	-0.085	-0.193	-0.212	-0.169	-0.189
	(0.199)	(0.188)	(0.187)	(0.183)	(0.283)
Other	0.047	0.005	0.044	0.071	0.154
	(0.511)	(0.459)	(0.463)	(0.459)	(0.806)
Standardized SAT Math		-1.057***	-1.110***	-1.248***	-1.186***
		(0.133)	(0.135)	(0.135)	(0.236)
Standardized SAT Verbal		-0.454***	-0.402***	-0.313**	-0.317
		(0.106)	(0.107)	(0.106)	(0.185)
High School GPA		-0.466***	-0.441***	-0.447***	-0.595***
		(0.082)	(0.081)	(0.082)	(0.151)
Composite Self-Efficacy Score			0.053	0.039	0.045
			(0.043)	(0.043)	(0.067)
Composite Utility Score			0.138***	0.127**	0.135*
			(0.042)	(0.041)	(0.064)
Composite Interest Score			-0.086*	-0.061	-0.082
			(0.041)	(0.040)	(0.062)
% URM in Class				0.220	0.174
				(0.117)	(0.175)
% Women in Class				0.116	0.159
				(0.143)	(0.226)
% Low Income in Class				0.061	-0.006
				(0.141)	(0.211)
Average SAT Verbal Score of Class				-0.378	-0.444

				(0.274)	(0.378)
Average SAT Math Score of Class				0.957***	0.942**
				(0.234)	(0.364)
Average High School GPA of Class				-0.237	-0.183
				(0.163)	(0.238)
High School Fixed Effects					X
R-sq	0.055	0.155	0.165	0.188	0.553
N	1355	1355	1355	1355	1355

Note. Overestimation is calculated as the difference between what students predicted they would receive in the course and their actual performance. Sample limited to non-transfer, STEM-aspiring students who took at least one STEM gateway courses during fall 2013 with valid overestimation survey measure and course grades. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3
Relationship between High School Ranking and Overestimation

	Overestimation
	(1)
API score: Quartile 4	0.046
	(0.163)
API score: Quartile 3	0.029
	(0.203)
API score: Quartile 2	-0.184
	(0.216)
API score: Quartile 1	0.640*
	(0.306)
Title I Status and School Urbanicity[a]	X
Demographic Characteristics	X
High School Performance	X
Non-Academic measures	X
Class Composition Measures	X
R-sq	0.226
N	1091

Note. The reference group is students from California high schools with the highest-ranking score. Sample limited to non-transfer, non-international STEM-aspiring students with valid API scores. Excluded from this sample are those who are international students, out-of-state students, students who attended small schools or mixed grade-level schools.
[a] Title I status is a measure of the extent to which the school received federal funds for enrolling large population of low-income students. Urbanicity is a measure of school locale. Both measures are from the Common Core of Data.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.

Changes in Beliefs about Grade Performance from Fall 2013 to Winter 2014

	Fall 2013					Winter 2014				
	Pre: What grade do you expect to receive in this course?		Actual Grade		Gap	Pre: What grade do you expect to receive in this course?		Actual Grade		Gap
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
All	10.17	(1.20)	6.32	(2.39)	3.84	9.64	(1.53)	6.47	(2.48)	3.18
RM	9.97	(1.21)	5.19	(2.36)	4.78	9.26	(1.58)	5.67	(2.53)	3.58
Non-RM	10.24	(1.18)	6.72	(2.27)	3.51	9.78	(1.49)	6.75	(2.41)	3.03

Note. Fall 2014 sample is 1831. Winter 2014 sample is 626. This survey item ranges from 0-12 with 0 = F, 1=D-, 2=D, 3=D+, 4=C-, 5=C, 6=C+, 7=B-, 8=B, 9=B+, 10=A-, 11=A, 12=A+. Sample is limited to non-transfer, STEM-aspiring students who took at least one STEM gateway courses and who responded to the survey question during both fall 2013 and winter 2014, with valid course grades and overestimation survey measure. Underrepresented-in-STEM racially minoritized students are those who identify as Black, Latinx, Pacific Islander, or Native American. We averaged the responses of students who took multiple STEM courses and therefore responded to the survey multiple times. Standard deviations are in parenthesis.

Table 5

Association between Overestimation and Interest in the Course

	(1) Full Sample	(2) RM	(3) Represented
Overestimation	-0.039***	-0.026	-0.047***
	(0.010)	(0.017)	(0.012)
Joint Test of Equality		p = 0.319	
Demographic	X	X	X
Prior Academic Achievement	X	X	X
Non-Academic Measures	X	X	X
Class Composition	X	X	X
R-sq	0.400	0.404	0.414
N	1091	294	797

Note. Interest measure is a composite score of three survey items: *I find many topics in this course to be interesting; Solving problems in this class is interesting for me; I find this class intellectually stimulating*. Sample limited to non-transfer, STEM-aspiring students who took at least one STEM gateway courses during fall 2013 and who responded to the survey question related to interest. All analyses include demographic predictors, prior academic achievement measures, non-academic measures (pre-survey composite measure of self-efficacy, utility, and task value) and class composition measures.

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

Table 6

Association between Overestimation and STEM Attrition

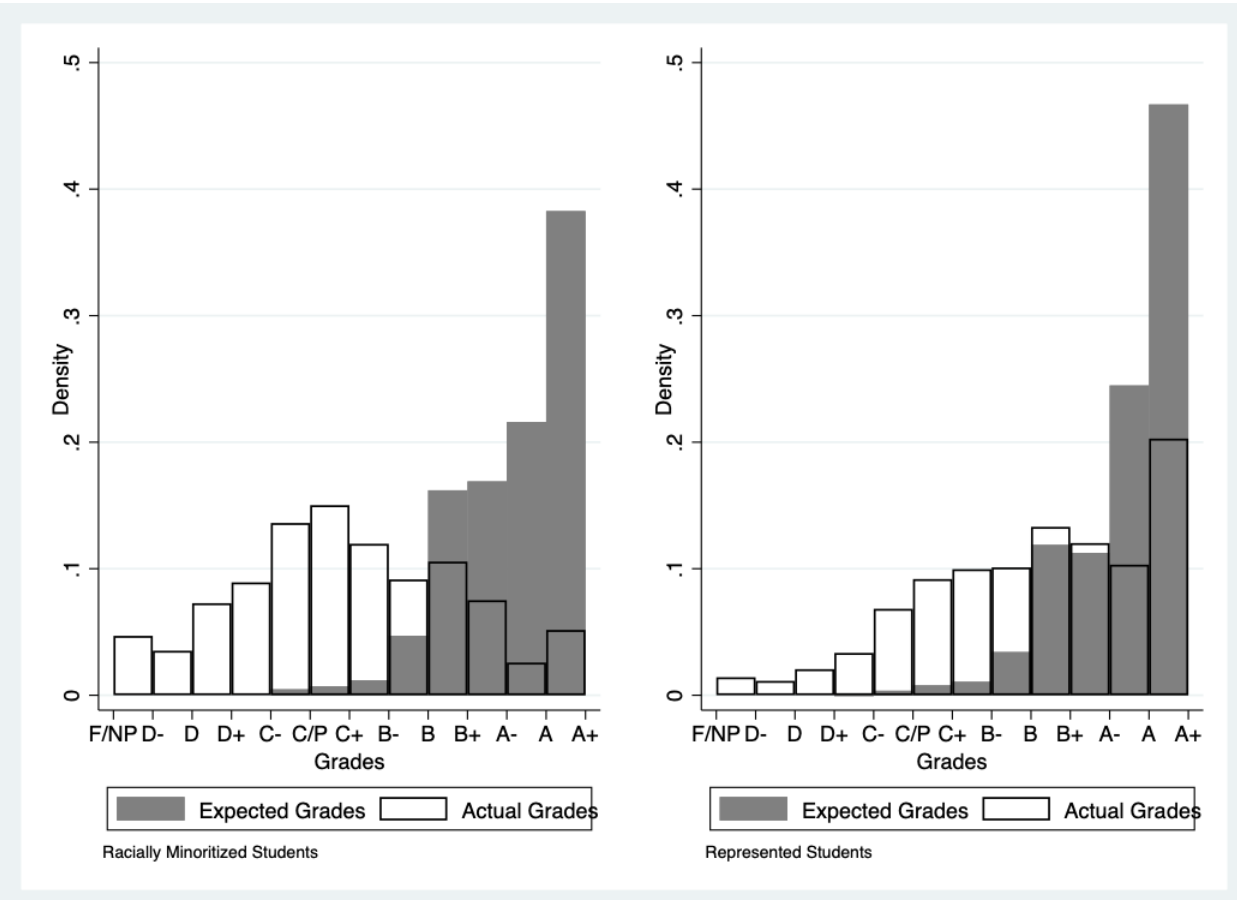
	(1)	(2)	(3)
	Full Sample	Racially Minoritized	Represented
Overestimation	0.060***	0.067***	0.057***
	(0.006)	(0.010)	(0.007)
Joint Test of Equality		p = 0.411	
Demographic	X	X	X
Prior Academic Achievement	X	X	X
Non-Academic Measures	X	X	X
Class Composition	X	X	X
R-sq	0.174	0.202	0.150
N	1343	370	973

Note. Attrition is defined as switching out of STEM as no student in our sample dropped out of college. The data includes six academic school years. The sample is limited to students who entered college with an initial major in STEM.

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

Figure 1

Distribution of the Gap between Predicted Grades and Actual Grades among Racially Minoritized Students and Represented Students



Note. These results are based on student survey responses from 71 sections across 33 courses at one institution during fall 2013.

Appendix

Table A.1

List of STEM majors in the analytical sample

AEROSPACE ENGR	Aerospace Engineering
BIOLOGICAL SCIENCES	Biological Sciences
BIOLOGY/EDUCATION	Biology/Education
BIOMED ENGR: PREMED	Biomed Engr: Pre-med
BIOMEDICAL ENGR	Biomedical Engineering
CHEMICAL ENGINEERING	Chemical Engineering
CHEMISTRY	Chemistry
CIVIL ENGINEERING	Civil Engineering
COMPUTER ENGINEERING	Computer Engineering
COMPUTER GAME SCI	Computer Science
COMPUTER SCI & ENGR	Computer Sci & Engr
COMPUTER SCIENCE	
EARTH SYSTEM SCIENCE	Earth System Science
ECOLOGY & EVOL BIO	Ecology & Evol Biology
ELECTRICAL ENGR	Electrical Engineering
ENVIRONMENTAL ENGR	Environmental Engr
ENVIRONMENTAL SCI	Environmental Sci
INFORMATICS	Informatics
MATERIALS SCI ENGR	Materials Science Engr
MATHEMATICS	Mathematics
MECHANICAL ENGR	Mechanical Engineering
NURSING SCIENCE	Nursing Science
PHARMACEUTICAL SCI	Pharmaceutical Science
PHYSICS	Physics
PUB HEALTH POLICY	Public Health Policy
PUB HEALTH SCIENCES	Pub Health Sciences
QUANTITATIVE ECON	Quantitative Econ
SOFTWARE ENGINEERING	Software Engineering
UNDECLARED-School of Engineering	Undeclared-School of Engineering
UNDECLARED-School of Information and Computer Sciences	Undeclared-School of Information and Computer Sciences
UNDECLARED-School of Physical Sciences	Undeclared-School of Physical Sciences

Table A.2
Survey Items

Please answer the following questions about **this course.** (Scale range – not at all true – very true of me)
Interest:
I find this class intellectually stimulating.
I find many topics in this course to be interesting.
Solving problems in this class is interesting for me.

Self-Efficacy:
I'm certain I can master the skills taught in this class.
I'm certain I can figure out how to do the most difficult course material.
I can do almost all the work in this class if I don't give up.

Utility:
Understanding the material has many benefits for me.
Having a solid background in the material taught in this class is worthless.
After I graduate, an understanding of the material taught in this class will be useless to me.

Calibration
What grade do you expect to receive in **this course?**

Table A.3

Miscalibration Patterns by Department

	Predicted		Actual		
	Mean	SD	Mean	SD	Gap
Biology	9.79	1.52	7.48	2.73	2.31
Chemistry	9.56	1.63	7.02	3.08	2.54
Engineering and Computer Science	10.29	1.35	8.14	2.77	2.15
Math	10.18	1.41	6.56	3.24	3.62
Physics	10.01	1.43	8.31	2.66	1.70

Table A.4

Predictors of Overestimation Focusing on Latinx Students

	Demographics (1)	Prior Achievement (2)	Non-Academic (3)	Class Composition (4)	High School Fixed Effects (5)
Latinx	0.850***	0.376	0.411	0.324	-0.092
	(0.236)	(0.226)	(0.230)	(0.226)	(0.358)
First Generation	0.387**	0.104	0.122	0.148	0.129
	(0.147)	(0.143)	(0.144)	(0.142)	(0.228)
Low Income	0.063	-0.143	-0.146	-0.158	-0.119
	(0.138)	(0.135)	(0.135)	(0.134)	(0.218)
Women	0.278*	0.034	0.063	0.130	0.285
	(0.126)	(0.124)	(0.127)	(0.135)	(0.209)
Asian	-0.086	-0.192	-0.211	-0.173	-0.288
	(0.200)	(0.188)	(0.187)	(0.183)	(0.284)
Other	0.047	0.009	0.051	0.066	0.078
	(0.511)	(0.459)	(0.463)	(0.460)	(0.806)
Standardized SAT Math		-1.057***	-1.112***	-1.243***	-1.153***
		(0.134)	(0.135)	(0.136)	(0.242)
Standardized SAT Verbal		-0.474***	-0.422***	-0.333**	-0.350
		(0.106)	(0.107)	(0.106)	(0.187)
High School GPA		-0.449***	-0.424***	-0.435***	-0.572***
		(0.082)	(0.082)	(0.082)	(0.153)
Composite Self-Efficacy Score			0.055	0.044	0.046
			(0.044)	(0.043)	(0.068)
Composite Utility Score			0.142***	0.133**	0.148*
			(0.042)	(0.041)	(0.065)
Composite Interest Score			-0.087*	-0.064	-0.085
			(0.041)	(0.041)	(0.063)
% URM in Class				0.240*	0.163
				(0.119)	(0.178)
% Women in Class				0.101	0.118
				(0.146)	(0.229)
% Low Income in Class				0.081	0.015
				(0.143)	(0.214)
Average SAT Verbal Score of Class				-0.406	-0.418
				(0.278)	(0.386)

Average SAT Math Score of Class				0.899***	0.869*
				(0.240)	(0.372)
Average High School GPA of Class				-0.160	-0.151
				(0.167)	(0.248)
High School Fixed Effects					X
R-sq	0.051	0.152	0.163	0.185	0.549
N	1313	1313	1313	1313	1313

Note. Overestimation is calculated as the difference between what students predicted they would receive in the course and their actual performance. For example, a student who severely overestimated by expecting to receive an A- in the course but ended up with a D would be flagged as having a grade gap of 7. Sample limited to non-transfer, STEM-aspiring Latinx students who took at least one STEM gateway courses during fall 2013 with valid overestimation survey measure and course grades.

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

Table A.5.

Association between Overestimation and Interest in the Course, Latinx Students

	(1)	(2)	(3)
	Full Sample	Latinx	Represented
Overestimation	-0.041***	-0.033	-0.047***
	(0.010)	(0.017)	(0.012)
		p = 0.5121	
Joint Test of Equality		p=0.512	
Demographic	X	X	X
Prior Academic Achievement	X	X	X
Non-Academic Measures	X	X	X
Class Composition	X	X	X
R-sq	0.402	0.411	0.414
N	1055	258	797

Note. Overestimation is calculated as the difference between what students predicted they would receive in the course and their actual performance. Interest measure is a composite score of three survey items: *I find many topics in this course to be interesting; Solving problems in this class is interesting for me; I find this class intellectually stimulating*. Sample limited to non-transfer, STEM-aspiring Latinx students who took at least one STEM gateway courses during fall 2013 and who responded to the survey question related to interest. All analyses include demographic predictors, prior academic achievement measures, non-academic measures (pre-survey composite measure of self-efficacy, utility, and task value) and class composition measures.

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

Table A.6.

Association between Overestimation and STEM Attrition, Latinx Students

	(1) Full Sample	(2) Latinx	(3) Represented
Overestimation	0.059***	0.056***	0.060***
	(0.006)	(0.012)	(0.007)
Joint Test of Equality		p = 0.784	
Demographic	X	X	X
Prior Academic Achievement	X	X	X
Non-Academic Measures	X	X	X
Class Composition	X	X	X
R-sq	0.167	0.180	0.153
N	1259	318	941

Note. Overestimation is calculated as the difference between what students predicted they would receive in the course and their actual performance. Attrition is defined as switching out of STEM as no student in our sample dropped out of college. The data includes six academic school years. The sample is limited to students who entered college with an initial major in STEM.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7.
Miscalibration Patterns, Non-Binary Race Categorization

	Fall 2013					
	Mean	SD	Min	Max	N	Gap
White: Predicted Grade	10.23	1.35	4	12	235	2.07
White: Actual Grade	8.16	2.67	0	12	235	
Black: Predicted Grade	10.35	1.10	7	12	42	4.08
Black: Actual Grade	6.27	3.29	0	12	42	
Latinx: Predicted Grade	9.67	1.46	4	12	376	4.12
Latinx: Actual Grade	5.55	2.77	0	11.5	376	
American Indian/Pacific Islander: Predicted Grade	10.19	1.41	8	12	8	4.56
American Indian/Pacific Islander: Actual Grade	5.63	2.30	2.5	9	8	

Note. This survey item ranges from 0-12 with 0 = F, 1=D-, 2=D, 3=D+, 4=C-, 5=C, 6=C+, 7=B-, 8=B, 9=B+, 10=A-, 11=A, 12=A+. We have coded students' actual grades to match the survey item range. SD = Standard Deviation.