



## The Role of Student Beliefs in Dual-Enrollment Courses

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Dual-enrollment courses are theorized to promote students' preparedness for college in part by bolstering their beneficial beliefs, such as academic self-efficacy, educational expectations, and sense of college belonging. These beliefs may also shape students' experiences and outcomes in dual-enrollment courses, yet few if any studies have examined this possibility. We study a large dual-enrollment program created by a university in the Southwest to examine these patterns. We find that mathematics self-efficacy and educational expectations predict performance in dual-enrollment courses, even when controlling for students' academic preparedness, while factors such as high school belonging, college belonging, and self-efficacy in other academic domains are unrelated to academic performance. However, we also find that students of color and first-generation students tend to have lower self-efficacy and educational expectations before enrolling in dual-enrollment courses, in addition to having lower levels of academic preparation. These findings suggest that students from historically marginalized populations may benefit from social-psychological as well as academic supports in order to receive maximum benefits from early postsecondary opportunities such as dual-enrollment. Our findings have implications for how states and dual-enrollment programs determine eligibility for dual-enrollment as well as how dual-enrollment programs should be designed and delivered in order to promote equity in college preparedness.

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## Introduction

College enrollment and attainment rates have been steadily increasing for all demographic groups over the past few decades (see National Center for Education Statistics, 2021, Table 302.20), yet considerable racial and socioeconomic gaps in the selectivity of colleges students enroll in (Baker et al., 2018; Carnevale & Strohl, 2013) and degree attainment (Shapiro et al., 2019) persist. One of many factors contributing to disparities in college access and attainment is inequalities in the rigor of high school courses students complete. While academic preparation is one of the strongest pre-college predictors of postsecondary success (Adelman, 1999, 2006; Cabrera & La Nasa, 2000, 2001; Terenzini et al., 2001), access to rigorous courses in high school such as Advanced Placement (AP), International Baccalaureate (IB), and dual-enrollment continues to be stratified on racial and socioeconomic lines (Kolluri, 2018; Museus et al., 2007; Perna et al., 2015; Prescott, 2006; Pretlow & Wathington, 2013).

A primary rationale for expanding access to courses such as dual-enrollment is the non-academic benefits they may provide. Dual-enrollment has been conceptualized as a form of “anticipatory socialization” where high school students can become familiar with the roles and routines of taking college-level courses (Karp, 2012). Success in these courses may raise students’ college aspirations and expectations, promote their sense of self-efficacy to succeed in future college-level coursework, develop their feelings of future belonging in college, and strengthen their identity as college students. However, these courses may be academically demanding, and success is not guaranteed. Indeed, experimental research where access to college-level coursework was expanded to new populations of students has found that these courses caused students higher levels of stress, decreased students’ confidence to succeed in college-level science courses, and reduced high school GPAs (Conger et al., 2019). These

findings lend urgency to the question: How do students' beliefs about themselves shape their experiences in college-level courses in high school, particularly for students from populations historically excluded from such opportunities?

This question is important for two reasons. First, research has found that students' beliefs predict their future academic outcomes, even when controlling for prior academic performance. This research has laid the groundwork for a variety of social-psychological interventions that promote students' utility-value (Hulleman et al., 2010), belonging (Murphy et al., 2020; Walton & Cohen, 2011), and growth mindset (Yeager et al., 2016; Yeager et al., 2019) that have been found to improve later academic outcomes. However, which beliefs matter most, for which populations, and in which educational contexts is a perennial question. For example, *grit* (Duckworth et al., 2007), operationalized as passion plus perseverance, has been found to predict many educational and life outcomes (Duckworth & Seligman, 2006; Eskreis-Winkler et al., 2014), but some studies suggest the power of grit for predicting academic achievement is limited when accounting for other beliefs and behaviors, such as self-regulation and engagement variables (Dixson, 2021; Muenks et al., 2017). In short, students' beliefs matter to their academic performance, interventions that shape students' psychologies can positively impact their academic experiences and outcomes, and intervening on the right constructs is of paramount importance.

Second, most states restrict access to college-level courses in high school to only those students who are "academically prepared" (Taylor et al., 2015; Zinth & Barnett, 2018). These eligibility policies presume that students below a certain threshold of academic proficiency will receive limited benefits (or harm) from participating in rigorous coursework. Reformers have recommended broadening access to college-level courses in high school by reducing academic

eligibility requirements in order to promote equity (Barnett et al., 2015; Hughes et al., 2012; Karp, 2012; Museus et al., 2007; Zinth & Barnett, 2018). However, this may pose an increased risk of students encountering difficulties in these courses (Conger et al., 2019; Hughes & Edwards, 2012). Indeed, the expansion of dual-enrollment programs has resulted in high failure rates, inequitable outcomes, and school-level discontinuation of the programs in some contexts (Hemelt & Swiderski, 2021). Identifying non-academic characteristics that contribute to students' success in early postsecondary opportunities (EPSO) such as dual-enrollment may be a key strategy for designing policies, programs, and interventions that expand access while ensuring students receive maximal benefit from these courses.

The purpose of this study is to address this gap using a dual-enrollment program created by a research university in the Southwest referred to as College Ready Now (CRN, a pseudonym). CRN administers a survey to all students at the beginning of the year that measures key non-academic characteristics the literature suggests are predictive of college access and success, such as college aspirations and expectations, course-specific academic self-efficacy, and perceived future belonging in college. By linking this survey data with administrative records on student performance and using structural equation modeling (SEM) techniques, we identify the extent to which these non-academic characteristics predict student performance in these courses. Our results show that students' self-efficacy and their college expectations predict their performance in dual-enrollment courses, even when controlling for their initial performance.

### **Dual-Enrollment and College Outcomes**

A large and growing body of literature has highlighted the benefits of dual-enrollment courses in terms of promoting students' enrollment, persistence, and attainment in postsecondary education. Although some studies have estimated limited effect of participation in dual-

enrollment on college outcomes (Speroni, 2011), the majority of empirical, quantitative studies using experimental or quasi-experimental designs have estimated that participation in dual-enrollment promotes college access and success overall (An, 2013a, 2013b; An & Taylor, 2019; Giani et al., 2014; What Works Clearinghouse, 2017) or increases enrollment in four-year institutions specifically (Hemelt et al., 2020). Early college high schools (ECHS), where students can take a large number of dual-enrollment courses and potentially even earn an associate's degree during high school, have similarly been found to significantly improve students' likelihood of college enrollment and degree attainment (Edmunds et al., 2020; Haxton et al., 2016).

While the benefits of dual-enrollment participation on college outcomes are becoming increasingly apparent, less is known about the causal mechanisms linking participation in dual-enrollment with these outcomes. Three primary mechanisms have been proposed. First, the accumulation of college credits may give students a “head start” on their college career. Although the literature is mixed regarding the relationship between the “dosage” of dual-credit participation (i.e. the number of credits earned) and college outcomes (An, 2013a; An & Taylor, 2019; Giani et al., 2014; Karp, 2007; Tobolowsky & Ozuna, 2016), students who earn college credits in high school are closer to completing their degree than their peers without college credits. This could also induce students to enroll in college by changing their cost-benefit calculations; earning a college degree takes less time and money if a student has already earned college credits before graduating high school. Congruent with this hypothesis, studies have found that students who participate in dual-enrollment in high school experience a higher likelihood of direct-to-college enrollment and greater credit accumulation, and this “academic momentum” explains much of the effect on subsequent persistence and attainment (Wang et al., 2015).

Second, dual-enrollment courses may be more academically challenging than traditional high school courses. Participating in dual-enrollment could steer students onto a path of more rigorous courses in high school and promote their success once they officially enroll in college. An experimental evaluation of a dual-enrollment advanced algebra course in Tennessee found that students in schools randomly assigned to offering the dual-enrollment course were more likely to participate in AP courses later in high school and less likely to participate in remedial courses (Hemelt et al., 2020). These effects were even more pronounced for students from traditionally marginalized groups, such as Black and Hispanic students. Research has also found that students who participated in dual-enrollment earned higher college GPAs than observably equivalent peers who did not participate in dual-enrollment (An, 2013b; Wang et al., 2015).

Third, dual-enrollment has been conceptualized as a form of *anticipatory socialization* in which high school students “try on” the role and identity of a college student (Karp, 2012). Experiencing success in college-level coursework may promote students’ college aspirations, academic self-efficacy, and perceived future belonging in college (Ozuna Allen et al., 2020). This may be particularly important for students who have historically been marginalized from higher education, including students of color and low-income students. Research has found that students who participated in dual-enrollment and subsequently enrolled in college exhibited higher rates of motivation and engagement compared to their college peers who did not participate in dual-enrollment, and this explained some of the relationship between dual-enrollment and college performance (An, 2015).

Though the field has learned a great deal about the potential benefits of participation in dual-enrollment, there are three primary limitations in the extant research. First, although some exceptions exist (An, 2013a; Giani et al., 2014; Troutman et al., 2018), the majority of

quantitative studies on dual-enrollment have focused on estimating the “average treatment effect,” or the mean difference in college outcomes between dual-enrollment students and students who did not participate in dual-enrollment. Less emphasis has been placed on sources of heterogeneity in the benefits students receive from dual-enrollment (An & Taylor, 2019), which is critical to understand in order to effectively and strategically expand access to dual-enrollment to new populations of students.

Second, some of the conclusions regarding the causal mechanisms linking participation in dual-enrollment to college outcomes have been reached using samples and methods misaligned with those conclusions. For example, An’s (2015) analysis is one of the few to quantitatively investigate the role of students’ beliefs in explaining the benefits of dual-enrollment on college performance. He concluded that “dual enrollment tended to increase academic motivation even after [he] controlled for precollege motivation. This finding aligns with advocates’ contention that a key function of dual enrollment is to raise a student’s academic motivation” (p. 120). However, the sample used in this study was restricted to only those students who enrolled in college, and no controls were included for students’ baseline motivation and engagement before participating in dual-enrollment. Alternative explanations of this finding are that students who participate in dual-enrollment are more motivated or engaged to begin with, or that participation in college-level coursework could deter less motivated or engaged students to pursue college altogether if the experience led them to believe they were not “cut out” for college after all. The latter finding is congruent with other studies that have found negative effects of participation in college-level coursework in high school on students’ beliefs about themselves and their abilities (Conger et al., 2019).



Third, no research to date has quantitatively examined how students' beliefs about themselves shape their experiences in dual-enrollment courses. The notion of "college readiness" has expanded over time from a myopic focus on academic preparation to a more holistic conceptualization of the non-academic skills and beliefs that provide students with tools to navigate higher education (Conley, 2008). A growing body of experimental studies have found that interventions that target students' beliefs may be effective at promoting their success in college, particularly for students from historically marginalized populations (Hulleman et al., 2010; Yeager et al., 2016). Yet no research has explored the role of students' beliefs in dual-enrollment courses specifically. The following section more deeply reviews the literature on how student beliefs shape their academic outcomes, specifically in college.

### **Student Beliefs and College Success**

Although academic preparation is generally considered to exert the strongest influence on students' academic performance in college (Adelman, 1999, 2006; Galla et al., 2019; Harackiewicz et al., 2002), research has consistently shown that students' non-academic or "non-cognitive" beliefs play an important role in shaping their college outcomes (e.g., Conley, 2007, 2008; Fong et al., 2017; Paunesku et al., 2015). Participating in dual-enrollment may promote students' college access and success to the extent that the experience promotes beliefs that are correlated with persistence and attainment in higher education. However, the inverse is also true – if dual-enrollment courses are authentic early college experiences, these beliefs may be important predictors of student achievement in dual-enrollment. In the current study, we focus on three categories of beliefs that have been found to predict students' college outcomes, may be influenced by participation in dual-enrollment, and may shape students' effort and achievement

in dual-enrollment: educational aspirations/expectations, academic self-efficacy, and sense of belonging.

### **Educational Aspirations and Expectations**

Researchers have long contended that students' aspirations and expectations about their educational and economic futures are some of the strongest determinants of their life outcomes, and in particular their likelihood of enrolling in and completing college (Alexander et al., 2008; Andrew & Hauser, 2011; Morgan, 2005; Schneider & Saw, 2016). Indeed, expectations have been conceptualized as one of the primary factors motivating student achievement (Wigfield & Eccles, 2000). Students' college expectations positively predict college enrollment (e.g., Eccles et al., 2004) and college success more generally (Cunningham et al., 2009; Mello, 2008) even when controlling for prior achievement.

Although related, aspirations and expectations are distinct both conceptually and in how they are measured: asking students how far in their education they aspire to go often elicits different responses compared to asking them how far they expect to go. Whereas roughly 80% of eleventh graders in the United States reported that they aspired to some level of postsecondary education after high school and 50-70% of all racial/ethnic groups aspired to a bachelor's degree or higher (Schneider & Saw, 2016), research in the United Kingdom has found that roughly a quarter of high school students report high aspirations but low expectations (Khattab, 2014; 2015). This "aspirations-expectations gap" has been identified among American middle school students as well (Kirk et al., 2012). One explanation for this gap is that students recognize the importance of postsecondary education and aspire to attain it but simultaneously recognize barriers that prevent them from realizing their aspirations. Lower achieving students (Khattab,

2014, 2015) and those from historically marginalized groups (Kirk et al., 2012) are more likely to exhibit this gap, congruent with this hypothesis.

Research has also found that college aspirations change throughout high school, and students' academic performance in high school classes is the factor most strongly associated with aspiration changes (DesJardins et al., 2019). Though yet to be demonstrated empirically, the effect of academic performance on college aspirations may be even more pronounced in college-level courses, given that students may interpret their performance in courses such as dual-enrollment to be a more accurate signal of their likelihood of success in college compared to traditional high school courses.

While college aspirations and expectations have been found to predict future college outcomes and to be influenced by academic performance in high school, research has yet to explore the extent to which college expectations are predictive of students' effort and experiences in dual-enrollment. If students have high aspirations or expectations to attend college, they may view their performance in dual-enrollment courses to be even more important compared to students with lower expectations – earning college credit in high school may be irrelevant to students who know they will never go to college. Conversely, the opposite may be true: students with high college expectations may feel less need to perform well in dual-enrollment courses if they are convinced they will attend college regardless of their performance, whereas students with low expectations may feel that they have to do well in their dual-enrollment course if they are to successfully transition into college. To date, no studies have empirically examined the relationship between college aspirations or expectations and performance in dual-enrollment.

### **Academic Self-Efficacy**

One of the strongest predictors of whether someone will do something is whether they believe that they are capable of doing it, a belief known as self-efficacy (Bandura, 1997). Self-efficacy beliefs, or one's confidence in her or his ability to accomplish a task, are among the strongest predictors of students' performance and persistence in academic contexts generally (Muenks et al., 2018) and college specifically (Chemers et al., 2001; Zajacova et al., 2005). Similar to educational expectations, the relationship between self-efficacy and academic outcomes is dynamic and reciprocal: students with higher academic self-efficacy are more likely to achieve a particular educational outcome conditional on their prior academic achievement (Schunk & Pajares, 2009), and *performance feedback* and *mastery experiences* are some of the most critical sources of self-efficacy (Talsma et al., 2018; Usher & Pajares, 2008).

Rather than a general belief such as academic self-concept, self-efficacy beliefs are specific to a particular task (Bandura, 1997). However, self-efficacy beliefs can be conceptualized and measured at different levels of granularity, and researchers have used various approaches to measure self-efficacy for predicting college outcomes. The College Self-Efficacy Inventory (Solberg et al., 1993) consists of 20 items related to class (e.g. academic) self-efficacy, social self-efficacy, and roommate self-efficacy. Studies have found these self-efficacy measures to be related to but empirically distinguished from adjacent measures such as occupational self-efficacy (Brown et al., 2000; Gore & Leuwerke, 2000) and career decision-making self-efficacy (Betz et al., 1996) (see Gore et al., 2005). In contrast, others measured students' self-efficacy in specific academic domains (e.g. math self-efficacy, science self-efficacy) to more accurately predict their academic performance in college courses (Wang & Lee, 2019). Subject-specific self-efficacy may be a more accurate predictor of performance in specific dual-enrollment courses (e.g. math self-efficacy predicting performance in math dual-enrollment courses)

compared to more general measures of self-efficacy for college success. Although approaches to its measurement differ, studies consistently show academic self-efficacy is predictive of performance in college.

The one caveat is that the timing of when self-efficacy is measured influences its predictive validity for college performance. Specifically, measuring self-efficacy beliefs before students begin college results in a weaker estimated relationship with academic performance compared to measuring self-efficacy after students' first-year of college (Gore, 2006). A leading explanation of this finding is that students' understanding of and confidence in their own abilities are less accurate before students begin college, which may be particularly true for students' whose educational experiences in high school were considerably less rigorous than their college experiences.

These theoretical considerations suggest three hypotheses about how academic self-efficacy may be related to students' dual-enrollment experiences. First, students' performance in dual-enrollment courses may bolster their college self-efficacy – students who perform well in dual-enrollment courses may become increasingly confident in their abilities to succeed in college. Second, self-efficacy may be an important predictor of performance in dual-enrollment courses just as it is for academic performance generally, even conditional upon prior or initial achievement. If students are confident in their abilities to succeed in their dual-enrollment course, they may exert more effort and remain more motivated compared to students with less confidence. However, Gore's (2006) research suggest that students' assessments of their abilities to succeed in college-level coursework may be inaccurate, particularly for high school students' enrolling in their first dual-enrollment course. This leads to a third hypothesis: there may be minimal or no relationship between self-efficacy measured before students' dual-enrollment

course and their performance in that course, particularly for high school students who have never enrolled in a college-level course. Empirical studies have yet to test these hypotheses.

### **Student Belonging**

Social belonging is defined as feeling socially connected and having positive relations with others (Walton & Cohen, 2007), and psychological sense of school belonging is defined as the extent to which students perceive themselves to be welcomed, valued, and respected members of the school community (Goodenow, 1993). A strong sense of school belonging has often been associated with higher grades, academic motivation, and high school completion rates and a lower propensity of school dropout and behavioral issues (Anderman, 2003; Finn, 1989; Goodenow, 1993a, 1993b; Osterman, 2000). In the college context, belonging has similarly been found to predict performance and persistence (Good et al., 2012; Hausmann et al., 2007; Strayhorn, 2018; Walton & Cohen, 2007, 2011), and longitudinal research has found that college students' daily experiences of belonging correlate strongly with their own emotional and behavioral engagement (Gillen-O'Neel, 2021). Sense of belonging in college may be particularly important for minoritized, low-income, and first-generation students who often experience lower sense of belonging and *stereotype threats* about their abilities to succeed in college (Ostrove & Long, 2007; Stebleton et al. 2014; Steele & Aronson, 1995; Steele et al., 2002; Walton & Cohen, 2007, 2011).

Dual-enrollment courses may be a particularly potent strategy for promoting students' sense of belonging in college through the *anticipatory socialization* dual-enrollment provides (Karp, 2012). Through dual-enrollment, high school students may register for a college course, be taught by a college instructor, receive their first college syllabus, earn a grade on a college transcript, and take classes on a college campus (though not all forms of dual-enrollment

combine all of these elements). All of these activities may lead to students feeling that they do in fact belong in a college environment, provided these experiences in dual-enrollment are positive. Dual-enrollment may therefore be particularly beneficial for students from populations or communities historically underrepresented in higher education due to its effect on students' sense of belonging in college.

But while dual-enrollment courses may promote college belonging, it is unclear if students' sense of belonging in college would predict their performance in dual-enrollment. Instead, it may be students' perceived belonging *in high school* that shapes their engagement and effort in their dual-enrollment classes, just as high school belonging influences students' motivation and academic performance in high school more generally (Finn, 1989; Goodenow, 1992; Osterman, 2000). To the authors' knowledge, studies to date have not empirically examined the extent to which belonging shapes students' experiences and outcomes in dual-enrollment courses or whether high school belonging vs. college belonging is a stronger predictor of these outcomes.

### **Summary of Literature on Student Beliefs and Dual-Enrollment**

The literature reviewed above suggests that educational aspirations and expectations, academic self-efficacy, and sense of belonging are both strong predictors of students' academic performance in high school and college and may be promoted by students' positive experiences in dual-enrollment courses, with historically underrepresented students theorized to benefit disproportionately from the experience. However, it is also likely that these beliefs may predict students' performance in dual-enrollment courses themselves. Given repeated calls to expand access to dual-enrollment courses to promote equity in participation (Barnett et al., 2015; Hughes et al., 2012; Karp, 2012; Museus et al., 2007; Zinth & Barnett, 2018) and policies that eliminated

academic eligibility requirements in the wake of COVID-19, understanding the extent to which students' beliefs shape their dual-enrollment experiences above and beyond academic background may inform policies, practices, and interventions that can promote students' beneficial beliefs. To date, no studies have empirically examined the relationship between students' beliefs and success in dual-enrollment. This study is designed to address this gap.

## **Methods**

### **Research Questions**

The study addresses three research questions:

- 1) To what extent do students' educational expectations, high school belonging, college belonging, and course-specific academic self-efficacy predict academic success in dual-enrollment courses?
- 2) Do these relationships vary across course subjects (STEM vs. non-STEM)?
- 3) To what extent do these beliefs predict end-of-semester grades controlling for students' early course performance?

### **Context – The CRN Program**

The sample for this study is drawn from CRN, a dual-enrollment program created by a research university in the Southwest. CRN currently offers thirteen college-level courses (only eleven were available at the time of this study) to high school students, allowing them to earn college credit from the university for successfully passing the course. A key factor that differentiates CRN from other dual-enrollment programs is that enrollment is not restricted to students who have previously demonstrated “college readiness” through performance on standardized assessments. Districts may apply additional eligibility criteria, such as completion of pre-requisite courses, but CRN itself does not impose these restrictions. This strategy provides



the opportunity for lower achieving students to enroll in CRN courses and for CRN to enroll a population of students that is highly reflective of the demographic diversity of the state in which it is located. The CRN population is more than two-thirds students of color, nearly one-half are low-income students, and more than one-half would be the first in their family to earn a bachelor's degree. Additional details on the characteristics of the sample are provided below. Roughly two-thirds of CRN participants earn college credit for their course each year.

### **Data Sources**

This study uses two data sources. The first is CRN's institutional data which includes demographic characteristics, course enrollments, and grades for students who participate in CRN courses. The second is a survey administered to all CRN students at the beginning of the year and is a required component of student orientation to the courses. This survey measures students' educational aspirations and expectations, sense of belonging in high school and college, and their self-efficacy in succeeding in college-level coursework. These measures are described further below.

### **Sample**

The sample consists of students who enrolled in an CRN course during the 2019-20 academic year, completed the beginning-of-year survey, and did not withdraw from the course ( $n = 23,833$ ). Less than half of one percent of student ( $n = 107$ ) did not have data on the first major assessment in the course, resulting in their exclusion from models containing that variable and a restricted sample of 23,726 for those analyses. The sample includes 1,046 teachers ( $k$ ) for an average of 22.8 students per teacher. In specific models, the sample is disaggregated into STEM vs. non-STEM courses to examine whether the relationship between student beliefs and course performance varies across course subjects. The STEM sample includes 691 teachers and 15,845

students enrolled in the following course subjects: Chemistry, College Algebra, Computer Science, Geoscience, Physics, Precalculus, and Statistics. The non-STEM sample includes 356 teachers and 7,881 students enrolled in the courses of Arts & Entertainment Technologies, History, and Rhetoric.

Demographically, the sample is 56% Hispanic/Latinx, 29% White, and between 4-6% for Asian, African-American/Black, and multiracial. Less than half of one percent of the sample is Native American or Native Hawaiian/Pacific Islander. Roughly 58% of the sample identified as female, 41% identified as male, and 0.3% identified as non-binary or another gender identity. Students who selected other for their gender were able to self-describe their gender in an open-ended response, but no self-described gender category was large enough to detect significant differences between that group and other gender categories. Exactly half of the sample would be the first in their family to earn a bachelor's degree, which is how first-generation students were defined.

### **Variables**

Our primary outcome variable is students' mid-term grade. We use mid-term rather than final grade for three reasons. First, there is a strong correlation between mid-term grade and final grade ( $r > .90$ ), which suggests the results would be similar whether we used mid-term or final grade. Second, using the mid-term grade rather than the final grade also allows us to retain students in the sample who may withdraw from the course after the first semester, particularly those who may withdraw once they determine they are unlikely to receive college credit for the course. Third, the Spring 2020 semester was the year that COVID-19 resulted in school closures and the sudden shift to remote learning, which may have biased our estimates using final grades.

This mid-term grade variable is standardized by course, so that 0 equals the mean grade in that course and 1 equals the standard deviation of grades in that course.

Our primary predictors are seven measures of students' beliefs gathered through the beginning-of-year survey: educational expectations, high school belonging, college belonging, and four measures of subject-specific academic self-efficacy. The educational expectations variable asked students: "How far in your education do you expect to get?" The response options included: drop out of high school, complete high school, attend college but do not complete a credential, complete a certificate or certification, complete an associate's degree, complete a bachelor's degree, complete a master's degree, and complete a doctoral degree. This variable was adapted from the National Center for Education Statistics' (NCES) High School Longitudinal Survey of 2009 (e.g. NCES, 2019).

The high school belonging measure contains four items that all begin with the stem: "High school is a place where..." followed by a statement on an agreement scale. The four items are: "I struggle to make friends" (reversed), "I make friends easily," "I feel like I belong," and "I feel awkward and out of place" (reversed). Two additional items were originally tested for inclusion in the construct before they were determined to load weakly onto the construct. Those items were: "I have had a high school teacher who has made a difference in my life," and "I feel like I have a teacher who cares about me." Both of these items loaded onto a separate construct that may be described as *teacher care*, but including this construct in the measurement model reduced fit.

The college belonging construct was measured by four items that ask students to first "take a moment to imagine [themselves] attending college." Students then indicate their agreement with the following statements: "I can see myself fitting in well with my college

peers,” “I can see myself feeling like I really belong in college,” “I can see myself feeling at home in the classroom or with my academics,” and “I can see myself feeling awkward and out of place” (reversed). Similar to the high school belonging construct, we also explored two additional items related to college belonging that asked students about their expected relationships with their professors: “I can see myself connecting well with my professors” and “I think some professors will care about me.” Once again, the exploratory model discussed below determined these items loaded onto a separate construct that may be referred to as *professor care*, but including this construct in the measurement model reduced fit.

The self-efficacy measures were adapted from Wang and Lee’s (2019) instrument designed to measure students’ self-efficacy in math and science in order to predict future interest in and pursuit of STEM in college. While Wang and Lee (2019) measured self-efficacy in math and science, we added self-efficacy measures for humanities and technology courses for a total of four subject-specific self-efficacy measures. Each measure included the same five items that asked students about their level of confidence in accomplishing various tasks in college-level courses in that subject. The five items were: “master the material taught in [subject],” “do well on exams in [subject],” “complete assignments successfully in [subject],” “receive a good grade in college [subject] courses,” and “perform well in course activities in [subject] classes.” Each item was measured on a five-point scale from “not at all confident” to “extremely confident.”

In addition to the constructs discussed above measured through student surveys, the models also control for a rich set of demographic covariates provided by CRN administrative records. Specifically, the statistical models control for race/ethnicity, gender, whether students would be the first in their families to complete college (“first-generation” students), whether students are native English speakers, access to technology at home (both as a proxy for

socioeconomic status and due to the online components of the course), graduation year, the course(s) students are enrolled in, and the teacher of the course. In models that control for students' early course performance, we add a variable that represents the grade students received on their first major assessment.<sup>1</sup> This "first exam" variable is standardized at the course level ( $M = 0$ ,  $SD = 1$ ) so that a score of zero represents the mean grade students received on that assessment in that course.

### **Statistical Analyses**

Although versions of the instruments we used to measure our constructs of interest had been developed and validated in prior research, we began with exploratory factor analysis (EFA) because some of the items had been modified and, to our knowledge, the instruments had not been piloted on students in dual-enrollment courses specifically. EFA examines the strength of covariance between items and underlying latent constructs which must be labeled and described by the researcher. As opposed to confirmatory factor analysis (CFA), EFA does not constrain items to load onto specific constructs, allowing the researcher to identify items that either load onto unintended factors or do not load strongly onto the intended construct.

Our EFA analysis proceeded in five steps. First, we randomly split the data into a 20% training sample and an 80% test sample. The EFA solution was first developed on the training sample and then applied to the test sample to ensure that the model did not overfit the data. Second, we added all of the survey items discussed above to the EFA model, conducted a GEOMIN oblique rotation (Browne, 2001; Yates, 1987), and removed items with loadings of less than 0.4 on all constructs and items that loaded weakly onto multiple factors (Worthington & Whittaker, 2006). Third, we conducted a parallel analysis to explore the relative fit of models

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<sup>1</sup> In general, math and science CRN courses use exams while humanities courses use essays as their major assessments.

that retained between six and nine factors with eigenvalues greater than 1.0. Fourth, we chose a six-factor model as the parallel analysis and model fit indices suggested that including more than six factors in the model reduced model fit. Fifth, we applied that six-factor model to the test data set, and the factor loadings and overall fit of the model to the test data were nearly identical to the training data, apart from one item that loaded onto a factor in the training data but not in the test data. This item was dropped because it did not significantly improve model fit, so we elected to proceed with the more parsimonious model. These steps led us to a measurement model with six latent factors (high school belonging, college belonging, math self-efficacy, science self-efficacy, humanities self-efficacy, and technological self-efficacy), discussed further in the results section.

After determining which items loaded onto which factors, we fit measurement models using confirmatory factor analysis (CFA) on the full sample as well as course specific subsamples. In CFA, the researcher(s) pre-define the constructs that will be measured and predetermine which items will load onto each factor. In addition to examining the factor loadings, the overall fit of the measurement model is assessed based on multiple model fit indices (Brown, 2006; Hu & Bentler, 1999; Jackson et al., 2009). Specifically, we used the chi-square goodness-of-fit index, the root mean square error of approximation (RMSEA; Steiger & Lind, 1980), the Tucker-Lewis index (TLI; Tucker & Lewis, 1973), the comparative fit index (CFI; Bentler, 1990), and the standardized root mean residual (SRMR; Kline, 2013). The cutoff criteria to indicate good model fit were a RMSEA value smaller than .06, a TLI and CFI value greater than .90, and SRMR less than 0.08 (Hu & Bentler, 1999; Kline, 2016).

We examined the relationship between our constructs of interest and student performance in dual-enrollment courses using multi-level structural equation modeling (SEM). Students were

treated as nested in the teachers who taught their CRN course, and the intercept varied randomly at the teacher-level. The outcome variable was the mid-term eligibility grade. The models include the educational expectations variable, the two latent belonging constructs, the four subject-specific self-efficacy measures, and the other student-level covariates discussed above. The first research question is addressed by fitting the SEM model to the full sample of students. We then fit separate models to the sub-samples of students in STEM and non-STEM courses to explore whether these relationships vary across courses, addressing the second research question. We add the first assessment grade variable to the model to address the third question and explore whether students' beliefs predict their mid-term grades even when controlling for their early performance in the course.

## **Results**

### **Exploratory Factor Analysis**

Table 1 contains the results of the EFA model with the final set of items. As discussed above, some items theorized to relate to high school belonging and college belonging were originally included in the model but loaded weakly onto the underlying constructs and reduced model fit. All items in the final EFA model produce a factor loading greater than 0.4 on the theoretically related construct and all loadings for that item are less than 0.4 on all other constructs. The reliability coefficients (Cronbach's alpha) are also listed at the bottom of the table. High school belonging and college belonging had reliabilities of approximately 0.83 and 0.84, respectively, and the four self-efficacy measures had reliabilities between 0.93-0.95.

[Table 1]

### **Confirmatory Factor Analysis (Measurement Model)**

The results of the CFA models are presented in Table 2. The table includes results for the model applied to the full sample as well as the two course-specific sub-samples. All of the items are statistically significantly related to the factor on which they load across all models. The factor loadings for the items that load onto the various self-efficacy constructs are all greater than 0.8, and the majority are greater than 0.9. The items indicating the high school belonging and college belonging constructs have somewhat smaller factor loadings, but the relationships between the items and the factors are still relatively strong. The loadings for the high school belonging items range from 0.656-0.849, and the loadings for college belonging items range from 0.773-0.893. The fit indices also suggest that the model provides strong fit to the data. Although the  $\chi^2$  test rejects the null hypothesis of good fit, this test is particularly sensitive to sample size (Bentler & Bonett, 1980; Hu & Bentler, 1999). The TLI and CFI values are both greater than 0.90, the SRMR is and the RMSEA is less than 0.05 across all models, suggesting good fit of the model to the data.

[Table 2]

### **Research Question #1 (All Courses)**

The results of our SEM model predicting students' mid-term credit eligibility grade are found in Table 3. This table includes the models for the full sample of students (RQ #1) as well as the two course-specific sub-samples (RQ #2). The models include the six latent constructs included in the CFA model, the educational expectations variable, and the remaining covariates discussed in the methods apart from the first exam variable, which is included in the next set of models.

We begin by examining the relationship between students' demographic characteristics and their academic performance. Our results show a number of statistically significant disparities



in the college grade students received in their course. For the full sample, African-American, Hispanic, and Native American students earn grades roughly 0.38, 0.23, and 0.19 SD lower than White students, respectively, and first-generation college students are estimated to earn a grade roughly 0.17 SD lower than continuing-generation students. In contrast, Asian students receive grades 0.25 SD higher than White students on average. We find minimal relationships between gender (0.03 SD) or being a native English speaker (0.02 SD) on course grades.

We similarly find limited evidence that certain beliefs make a substantial difference in terms of students' academic performance. Specifically, the estimates for college belonging, science self-efficacy, and humanities self-efficacy are all less than 0.05, which suggests minimal relationships. The estimates for high school belonging and technology self-efficacy are both statistically significantly related to the grade students earned, but both estimates are still relatively small (0.05-0.10) and, in fact, negative. If anything, students with higher levels of high school belonging and self-efficacy in technology courses are estimated to do worse in their dual-enrollment courses.

But two beliefs were found to be positively, significantly, and strongly related to students' academic performance: mathematics self-efficacy and educational expectations. Students who scored one SD higher on the mathematics self-efficacy construct received grades 0.28 SD higher across all courses and 0.38 SD higher in STEM courses specifically. This estimate for mathematics self-efficacy is roughly of the same magnitude of the racial and socioeconomic disparities in academic performance discussed above. Surprisingly, mathematics self-efficacy was also found to be positively and significantly related to students' performance in non-STEM courses (0.13 SD), roughly twice the estimate of humanities self-efficacy (0.06 SD). The estimates for the educational expectations variable also suggest this belief matters for how

students perform in dual-enrollment. A 1 SD increase in educational expectations corresponds to a 0.09 SD increase in students' grades.

[Table 3]

### **Student Beliefs and Academic Persistence**

The results of the previous analyses underscore two points. First, congruent with extensive prior literature, students' from historically marginalized populations tend to have lower academic performance compared to more privileged students. Second, at least some beliefs that students hold – in our case, mathematics self-efficacy and college expectations – appear to matter roughly as much as race and class. However, these models do not control for students' prior academic preparation. The disparities in academic performance could simply reflect disparities in academic preparation, and the apparent relationships between student beliefs and their performance in dual-enrollment could be due to omitting controls for academic background. Put differently, if higher achieving students tended to have higher mathematics self-efficacy and educational expectations and also performed better in dual-enrollment courses, our estimates of our belief measures could be biased.

To further scrutinize the importance of these beliefs, the next set of models adds the control variable that represents the grade students received on the first major assessment in the course. These results are found in Table 4. As expected, the grade students receive on their first major assessment in the course is strongly related to their end-of-semester grade. For each one SD increase in first assessment grade, students' final grade is estimated to increase by roughly 0.76 SD. The estimate is fairly consistent for both STEM (0.79 SD) and non-STEM (0.71 SD) courses. Controlling for students' first assessment grade also substantially shrinks the estimated demographic disparities in course performance. In these models, the estimates for African-

American (-0.10 SD), Hispanic (-0.06 SD), and first-generation (-0.07 SD) students are approximately one-half to one-third the magnitude of the estimates in the model without the first assessment control.

Similarly, controlling for first assessment considerably reduces the estimated relationships between students' beliefs and their end-of-semester grade. The estimates for the two belonging constructs and three of the four self-efficacy factors are all less than 0.03 SD, once again suggesting minimal relationships between these factors and mid-term grade. However, once again we find that mathematics self-efficacy and educational expectations are statistically significantly and importantly related to students' end-of-semester grade when controlling for first assessment. The estimate for mathematics self-efficacy in the full model (0.09 SD) and the model for STEM courses (0.11 SD) is of the same magnitude as the Black-White grade gap, and the estimate for educational expectations (0.04 SD) is also significantly related to end-of-semester grade.

[Table 4]

### **Student Demographics and Beliefs**

The previous analyses demonstrated that students' educational expectations and mathematics self-efficacy predict their grades in dual-enrollment courses even when controlling for initial academic performance, while beliefs such as college and high school belonging and other self-efficacy beliefs did not. We have yet to explore how these predictive beliefs actually vary across student groups. Table 5 presents descriptively how educational expectations and mathematics self-efficacy vary across students based on race/ethnicity and first-generation status. For mathematics self-efficacy, the first column includes the mean of the five items that comprise

the mathematics self-efficacy scale, while the second column reports those estimates in the form of standardized mean differences (i.e., effect sizes).

The results show that students from populations historically marginalized from higher education and rigorous high school coursework tend to have lower educational expectations and lower mathematics self-efficacy compared to their peers. More than 90% of White and Asian students expect to earn a bachelor's degree or higher, compared to 80-85% of Black, Hispanic/Latinx, and Native American students. First-generation students were 12 percentage points less likely to expect to earn a bachelor's degree or higher compared to continuing-generation students. Although the educational expectations are high for the entire sample, note that the population is drawn from students enrolled in a rigorous dual-enrollment course offered by the state's public flagship university. Similarly, Black and Hispanic/Latinx students expressed lower mathematics self-efficacy compared to White and Asian students – roughly 0.13 SD lower than White students and 0.16 SD lower than Asian students. Although Native American students reported the highest mathematics self-efficacy out of any racial/ethnic group, the samples for Native American and Native Hawaiian/Pacific Islander students was quite small, making this estimate noisy.

[Table 5]

### **Discussion**

Although dual-enrollment courses have been found to promote students' college readiness and success (An, 2013a, 2013b; An & Taylor, 2019; Giani et al., 2014; What Works Clearinghouse, 2017), whether dual-enrollment as a national strategy can reduce racial and socioeconomic inequalities in students' college enrollment and attainment is a critical question to examine given inequalities in the rates in which students participate in dual-enrollment (NCES,

2019). These inequalities in access are largely driven by academic eligibility requirements that disproportionately exclude historically marginalized populations (Taylor et al., 2015; Zinth & Barnett, 2018). The exclusionary effect of academic eligibility requirements has led to calls to eliminate these requirements in order to promote equitable access to dual-enrollment. However, expanding access to rigorous coursework may do more harm than good if the courses do not provide opportunities for students to thrive academically and psychologically in the rigors of college-level coursework (Conger et al., 2019). Understanding how students' non-academic characteristics shape their experiences in dual-enrollment is therefore a key question.

The purpose of this study was to examine how students' beliefs about themselves and their abilities predict their performance in dual-enrollment courses. We find that students' educational expectations and mathematics self-efficacy do indeed predict their end-of-term grades in dual-enrollment courses, even when accounting for their prior academic preparation as proxied by their performance early in the semester. The relationship between these beliefs and academic achievement is roughly of the same magnitude as some of the racial/ethnic and socioeconomic gaps found in students' performance in dual-enrollment courses. These findings support the long-standing contention that students' beliefs about themselves and their academic abilities inform students' motivation, effort, and persistence through academic challenge, above and beyond their prior academic preparation (Bandura, 1997; Wigfield & Eccles, 2000; Yeager & Dweck, 2012). However, we also find that some beliefs are more predictive than others, as constructs such as high school and college belonging did not predict academic performance, nor did self-efficacy in domains other than mathematics. The field should continue to explore which social-psychological factors appear to matter most in dual-enrollment courses, for which student populations, and under what educational conditions (e.g. courses taught online or in-person, at

the high school or the college campus, by a high school instructor or a college faculty, in which courses).

Unfortunately, we also find that students of color and first-generation students report lower educational expectations and mathematics self-efficacy compared to White and Asian students and continuing-generation students, respectively. On one hand, this is not surprising. Historically marginalized students are often confronted with stereotypes about their abilities and belonging in educational contexts that can dampen their academic achievement as well as their beliefs about themselves (Steele & Aronson, 1995; Steele et al., 2002). Nevertheless, this finding presents a quandary: academic eligibility requirements may reinforce and magnify inequalities in students' dual-enrollment participation, yet racial/ethnic and socioeconomic inequalities exist in students' non-academic characteristics as well.

We would like to underscore two ways in which we hope these findings *are not used by policymakers and dual-enrollment programs*. First, we do not believe that students' beliefs about themselves and their abilities should be used to screen students for participation in dual-enrollment, even if these beliefs are predictive of dual-enrollment performance. Not only were these measures not designed for that purpose, but this approach could also contribute to racial and socioeconomic inequalities in students' access to dual-enrollment. Second, we do not believe that these measures should be used as an outcome variable to measure the efficacy of dual-enrollment programs. Once again, not only were the measures not designed to be used as outcomes, the field has yet to explore how sensitive these belief measures are to change and how they are related to students' qualitative experiences in dual-enrollment. Although the original intent of the current study was to administer the same belief measures before and after students' dual-enrollment courses, the post-survey administration was cancelled due to COVID-19. Future

research must determine which non-academic measures are predictive of academic performance in dual-enrollment in addition to being both statistically reliable and sensitive to differences in program design and quality to measure dual-enrollment efficacy.

How, then, should these findings be applied to dual-enrollment programs? In our view, the most promising avenue is to examine how the characteristics of dual-enrollment programs, the ways in which these courses are designed and taught, training and professional development for teachers of dual-enrollment, and other student-level interventions and supports that may be integrated with dual-enrollment courses can promote these *beneficial beliefs*, particularly for historically marginalized students. For example, front-loading activities and assignments in dual-enrollment courses designed to promote students' academic self-efficacy may be a promising approach, as could be interventions intended to bolster students' educational expectation or reduce their aspirations-expectations gap. Professional development with dual-enrollment teachers could be designed and tested to examine how such training promotes the self-efficacy and educational expectations of students in dual-enrollment courses. Interventions that promote dual-enrollment students' growth mindset may be effective at promoting their academic achievement, as has been shown for students making the transition into high school (Yeager et al., 2019).

### **Conclusion**

This study has demonstrated that many of the beliefs hoped to be promoted through students' participation in dual-enrollment programs, such as self-efficacy and educational expectations, are themselves predictive of student performance in dual-enrollment. However, these findings are correlational rather than causal, and our estimates are likely influenced by omitted variable bias. Future research should continue to explore which beliefs matter most –

and for whom – in shaping students’ experiences and outcomes in dual-enrollment and other early college opportunities for high school students, and what curricular, pedagogical, and psychological practices and interventions can promote these beliefs. We believe this is a promising line of inquiry for promoting equity in both access and outcomes in dual-enrollment courses.



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## Tables and Figures

Table 1: Exploratory Factor Analysis

| Item     | HS<br>Belonging | College<br>Belonging | Math Self-<br>Efficacy | Sci. Self-<br>Efficacy | Hum. Self-<br>Efficacy | Tech. Self-<br>Efficacy |
|----------|-----------------|----------------------|------------------------|------------------------|------------------------|-------------------------|
| HSSTRUG  | 0.929*          | -0.082*              | -0.014*                | 0.004                  | 0.038*                 | 0.003                   |
| HSFREASY | 0.810*          | 0.048*               | -0.024*                | -0.003                 | 0.029*                 | 0.007                   |
| HSIBEL   | 0.478*          | 0.311*               | 0.035*                 | 0.022                  | -0.074*                | -0.004                  |
| HSAWK    | 0.540*          | 0.182*               | 0.059*                 | -0.019                 | -0.048*                | -0.007                  |
| CLGPEERS | 0.216*          | 0.641*               | -0.014                 | 0.014                  | 0.019                  | 0.013                   |
| CLGIBEL  | 0.039*          | 0.756*               | -0.014                 | 0.018                  | 0.012                  | 0.009                   |
| CLGCONN  | 0.001           | 0.695*               | 0.003                  | 0.008                  | 0.024*                 | 0.022                   |
| CLGCLASS | -0.051*         | 0.751*               | 0.043*                 | -0.003                 | 0.037*                 | -0.006                  |
| MEXAM    | 0.006           | -0.010               | 0.867*                 | -0.013                 | -0.037*                | 0.003                   |
| MMASTER  | -0.029*         | 0.029*               | 0.883*                 | -0.040*                | -0.055*                | 0.003                   |
| MGRADE   | -0.003          | -0.002               | 0.832*                 | 0.022*                 | 0.042*                 | 0.016                   |
| MATHACT  | 0.030*          | 0.000                | 0.834*                 | 0.035*                 | 0.034*                 | 0.019*                  |
| MASSIGN  | 0.012           | 0.008                | 0.754*                 | 0.051*                 | 0.053*                 | -0.010                  |
| SEXAM    | 0.003           | 0.017                | 0.013                  | 0.861*                 | -0.031*                | -0.014                  |
| SMMASTER | -0.024*         | 0.032*               | -0.007                 | 0.888*                 | -0.057*                | -0.010                  |
| SGRADE   | 0.019*          | -0.033*              | 0.030*                 | 0.848*                 | 0.047*                 | 0.001                   |
| SACT     | 0.007           | 0.006                | -0.006                 | 0.849*                 | 0.030*                 | 0.033*                  |
| SASSIGN  | 0.003           | 0.005                | 0.008                  | 0.813*                 | 0.038*                 | 0.026*                  |
| HEXAM    | 0.006           | 0.023*               | -0.004                 | 0.015                  | 0.849*                 | -0.006                  |
| HMASTER  | -0.015          | 0.049*               | -0.021*                | -0.008                 | 0.873*                 | -0.022*                 |
| HGRADE   | 0.000           | -0.014               | 0.021*                 | 0.020*                 | 0.897*                 | 0.012                   |
| HACT     | 0.015*          | -0.009               | 0.015                  | -0.001                 | 0.907*                 | 0.017*                  |
| HASSIGN  | 0.005           | 0.009                | 0.016                  | 0.009                  | 0.855*                 | 0.028*                  |
| TEXAM    | 0.018*          | -0.001               | 0.015                  | 0.006                  | -0.014*                | 0.896*                  |
| TMASTER  | -0.006          | 0.024*               | 0.000                  | -0.011                 | -0.029*                | 0.908*                  |
| TGRADE   | 0.001           | 0.000                | 0.004                  | 0.015*                 | 0.017*                 | 0.911*                  |
| TACT     | -0.003          | 0.000                | 0.001                  | -0.002                 | 0.024*                 | 0.922*                  |
| TASSIGN  | -0.004          | -0.003               | 0.006                  | 0.019*                 | 0.020*                 | 0.887*                  |
| Alpha    | 0.83            | 0.84                 | 0.96                   | 0.94                   | 0.93                   | 0.95                    |



Table 2: Measurement Model Confirmatory Factor Analysis

|                                 | All Courses |       |       | STEM Courses |       |       | Non-STEM Courses |       |       |
|---------------------------------|-------------|-------|-------|--------------|-------|-------|------------------|-------|-------|
|                                 | B           | SE    | p     | B            | SE    | p     | B                | SE    | p     |
| <i>HS Belonging</i>             |             |       |       |              |       |       |                  |       |       |
| HSBSTRUG                        | 0.844       | 0.003 | 0.000 | 0.847        | 0.004 | 0.000 | 0.838            | 0.005 | 0.000 |
| HSBFEASY                        | 0.849       | 0.004 | 0.000 | 0.854        | 0.004 | 0.000 | 0.841            | 0.006 | 0.000 |
| HSBIBELG                        | 0.661       | 0.006 | 0.000 | 0.658        | 0.007 | 0.000 | 0.670            | 0.011 | 0.000 |
| HSBAWAK                         | 0.656       | 0.006 | 0.000 | 0.651        | 0.008 | 0.000 | 0.668            | 0.012 | 0.000 |
| <i>College Belonging</i>        |             |       |       |              |       |       |                  |       |       |
| CLPEER                          | 0.893       | 0.002 | 0.000 | 0.891        | 0.002 | 0.000 | 0.899            | 0.003 | 0.000 |
| CLIBELG                         | 0.852       | 0.004 | 0.000 | 0.858        | 0.004 | 0.000 | 0.839            | 0.007 | 0.000 |
| CLCONN                          | 0.773       | 0.005 | 0.000 | 0.775        | 0.006 | 0.000 | 0.772            | 0.009 | 0.000 |
| CLCLASS                         | 0.790       | 0.005 | 0.000 | 0.798        | 0.006 | 0.000 | 0.775            | 0.009 | 0.000 |
| <i>Tech Self-Efficacy</i>       |             |       |       |              |       |       |                  |       |       |
| TEXAM                           | 0.917       | 0.001 | 0.000 | 0.918        | 0.002 | 0.000 | 0.916            | 0.002 | 0.000 |
| TMASTER                         | 0.915       | 0.002 | 0.000 | 0.915        | 0.002 | 0.000 | 0.916            | 0.003 | 0.000 |
| TGRADE                          | 0.935       | 0.002 | 0.000 | 0.934        | 0.002 | 0.000 | 0.936            | 0.003 | 0.000 |
| TACTIVITES                      | 0.942       | 0.001 | 0.000 | 0.941        | 0.002 | 0.000 | 0.944            | 0.002 | 0.000 |
| TASSIGN                         | 0.922       | 0.002 | 0.000 | 0.921        | 0.002 | 0.000 | 0.923            | 0.003 | 0.000 |
| <i>Science Self-Efficacy</i>    |             |       |       |              |       |       |                  |       |       |
| SEXAM                           | 0.900       | 0.001 | 0.000 | 0.900        | 0.002 | 0.000 | 0.900            | 0.002 | 0.000 |
| SMASER                          | 0.899       | 0.002 | 0.000 | 0.900        | 0.002 | 0.000 | 0.898            | 0.004 | 0.000 |
| SGRADE                          | 0.911       | 0.002 | 0.000 | 0.909        | 0.002 | 0.000 | 0.916            | 0.003 | 0.000 |
| SACTIVITES                      | 0.915       | 0.002 | 0.000 | 0.915        | 0.002 | 0.000 | 0.915            | 0.003 | 0.000 |
| SASSIGN                         | 0.887       | 0.002 | 0.000 | 0.882        | 0.003 | 0.000 | 0.896            | 0.004 | 0.000 |
| <i>Math Self-Efficacy</i>       |             |       |       |              |       |       |                  |       |       |
| MEXAM                           | 0.882       | 0.002 | 0.000 | 0.882        | 0.002 | 0.000 | 0.883            | 0.003 | 0.000 |
| MMASTER                         | 0.880       | 0.002 | 0.000 | 0.877        | 0.003 | 0.000 | 0.883            | 0.003 | 0.000 |
| MGOOD                           | 0.897       | 0.002 | 0.000 | 0.895        | 0.003 | 0.000 | 0.900            | 0.004 | 0.000 |
| MACTIVITES                      | 0.913       | 0.002 | 0.000 | 0.911        | 0.003 | 0.000 | 0.915            | 0.003 | 0.000 |
| MASSIGN                         | 0.845       | 0.003 | 0.000 | 0.839        | 0.004 | 0.000 | 0.854            | 0.004 | 0.000 |
| <i>Humanities Self-Efficacy</i> |             |       |       |              |       |       |                  |       |       |
| HEXAM                           | 0.907       | 0.001 | 0.000 | 0.906        | 0.002 | 0.000 | 0.911            | 0.002 | 0.000 |
| HMASTER                         | 0.907       | 0.002 | 0.000 | 0.903        | 0.002 | 0.000 | 0.913            | 0.003 | 0.000 |
| HGOOD                           | 0.929       | 0.002 | 0.000 | 0.931        | 0.002 | 0.000 | 0.925            | 0.003 | 0.000 |
| HACTIVITES                      | 0.935       | 0.002 | 0.000 | 0.937        | 0.002 | 0.000 | 0.933            | 0.003 | 0.000 |
| HASSIGN                         | 0.907       | 0.002 | 0.000 | 0.906        | 0.003 | 0.000 | 0.910            | 0.004 | 0.000 |
| Chi-Square                      | 398646      |       | 0.000 | 269743       |       | 0.000 | 132184           |       | 0.000 |
| RMSEA                           | 0.044       |       |       | 0.046        |       |       | 0.044            |       |       |
| CFI                             | 0.911       |       |       | 0.909        |       |       | 0.916            |       |       |
| TLI                             | 0.904       |       |       | 0.901        |       |       | 0.909            |       |       |

Table 3: Multilevel Structural Equation Model Predicting Mid-Term College Grade

|                          | All Courses |        |       | STEM Courses |        |       | Non-STEM Courses |       |       |
|--------------------------|-------------|--------|-------|--------------|--------|-------|------------------|-------|-------|
|                          | B           | SE     | p     | B            | SE     | p     | B                | SE    | p     |
| <i>Latent Factors</i>    |             |        |       |              |        |       |                  |       |       |
| High School Belonging    | -0.087      | 0.010  | 0.000 | -0.086       | 0.012  | 0.000 | -0.085           | 0.019 | 0.000 |
| College Belonging        | -0.036      | 0.015  | 0.020 | -0.055       | 0.018  | 0.002 | -0.019           | 0.029 | 0.511 |
| Tech Self-Efficacy       | -0.075      | 0.011  | 0.000 | -0.096       | 0.013  | 0.000 | -0.046           | 0.020 | 0.019 |
| Science Self-Efficacy    | -0.033      | 0.014  | 0.018 | -0.036       | 0.017  | 0.031 | -0.037           | 0.024 | 0.135 |
| Math Self-Efficacy       | 0.275       | 0.015  | 0.000 | 0.376        | 0.017  | 0.000 | 0.128            | 0.019 | 0.000 |
| Humanities Self-Efficacy | 0.004       | 0.012  | 0.746 | -0.034       | 0.013  | 0.010 | 0.063            | 0.021 | 0.002 |
| <i>Covariates</i>        |             |        |       |              |        |       |                  |       |       |
| YEAR                     | 0.170       | 0.019  | 0.000 | 0.198        | 0.022  | 0.000 | -0.008           | 0.035 | 0.811 |
| FIRSTGEN                 | -0.169      | 0.015  | 0.000 | -0.202       | 0.018  | 0.000 | -0.114           | 0.027 | 0.000 |
| GENDER                   | -0.033      | 0.014  | 0.023 | 0.011        | 0.017  | 0.511 | -0.123           | 0.026 | 0.000 |
| HOMELANG                 | 0.020       | 0.009  | 0.034 | 0.027        | 0.011  | 0.015 | 0.006            | 0.018 | 0.727 |
| TECHACCESS               | 0.073       | 0.008  | 0.000 | 0.071        | 0.010  | 0.000 | 0.076            | 0.014 | 0.000 |
| EXPECTATION              | 0.092       | 0.006  | 0.000 | 0.098        | 0.007  | 0.000 | 0.085            | 0.010 | 0.000 |
| R_AA                     | -0.376      | 0.031  | 0.000 | -0.387       | 0.037  | 0.000 | -0.352           | 0.056 | 0.000 |
| R_AM_INDIA               | -0.192      | 0.102  | 0.059 | -0.332       | 0.127  | 0.009 | 0.166            | 0.157 | 0.290 |
| R_ASIAN                  | 0.254       | 0.027  | 0.000 | 0.263        | 0.032  | 0.000 | 0.219            | 0.050 | 0.000 |
| R_HISPANIC               | -0.230      | 0.020  | 0.000 | -0.235       | 0.025  | 0.000 | -0.213           | 0.031 | 0.000 |
| R_HI_PACIF               | -0.391      | 0.234  | 0.095 | -0.259       | 0.247  | 0.295 | -0.699           | 0.524 | 0.183 |
| R_TWO_RACE               | -0.121      | 0.034  | 0.000 | -0.085       | 0.039  | 0.030 | -0.193           | 0.061 | 0.002 |
| COURSESCI                | 0.052       | 0.060  | 0.386 |              |        |       |                  |       |       |
| COURSEMATH               | -0.067      | 0.056  | 0.238 |              |        |       |                  |       |       |
| <i>n</i>                 |             | 23,933 |       |              | 15,845 |       |                  | 7,988 |       |
| <i>k</i>                 |             | 1046   |       |              | 691    |       |                  | 356   |       |

Table 4: Multilevel Structural Equation Model Predicting Mid-Term College Grade with Exam 1

|                          | All Courses |       |       | STEM Courses |       |       | Non-STEM Courses |       |       |
|--------------------------|-------------|-------|-------|--------------|-------|-------|------------------|-------|-------|
|                          | B           | SE    | p     | B            | SE    | p     | B                | SE    | p     |
| <i>Latent Factors</i>    |             |       |       |              |       |       |                  |       |       |
| High School Belonging    | -0.023      | 0.007 | 0.002 | -0.013       | 0.008 | 0.127 | -0.042           | 0.013 | 0.002 |
| College Belonging        | -0.003      | 0.009 | 0.754 | -0.007       | 0.011 | 0.529 | 0.001            | 0.019 | 0.943 |
| Tech Self-Efficacy       | -0.018      | 0.007 | 0.006 | -0.024       | 0.008 | 0.001 | -0.007           | 0.012 | 0.585 |
| Science Self-Efficacy    | -0.029      | 0.008 | 0.000 | -0.025       | 0.010 | 0.010 | -0.039           | 0.015 | 0.010 |
| Math Self-Efficacy       | 0.089       | 0.008 | 0.000 | 0.109        | 0.010 | 0.000 | 0.056            | 0.014 | 0.000 |
| Humanities Self-Efficacy | 0.007       | 0.007 | 0.345 | 0.000        | 0.008 | 0.976 | 0.019            | 0.015 | 0.205 |
| <i>Covariates</i>        |             |       |       |              |       |       |                  |       |       |
| First Exam               | 0.760       | 0.007 | 0.000 | 0.785        | 0.008 | 0.000 | 0.713            | 0.012 | 0.000 |
| EXPECTATIONS             | 0.038       | 0.004 | 0.000 | 0.037        | 0.005 | 0.000 | 0.039            | 0.008 | 0.000 |
| YEAR                     | 0.063       | 0.010 | 0.000 | 0.073        | 0.012 | 0.000 | 0.004            | 0.023 | 0.866 |
| FIRSTGEN                 | -0.070      | 0.009 | 0.000 | -0.073       | 0.012 | 0.000 | -0.062           | 0.017 | 0.000 |
| GENDER                   | -0.079      | 0.009 | 0.000 | -0.070       | 0.011 | 0.000 | -0.102           | 0.017 | 0.000 |
| HOMELANG                 | 0.020       | 0.006 | 0.001 | 0.019        | 0.007 | 0.003 | 0.019            | 0.011 | 0.078 |
| TECHACCESS               | 0.027       | 0.005 | 0.000 | 0.025        | 0.006 | 0.000 | 0.029            | 0.010 | 0.003 |
| R_AA                     | -0.100      | 0.021 | 0.000 | -0.073       | 0.025 | 0.003 | -0.146           | 0.038 | 0.000 |
| R_AM_INDIA               | 0.042       | 0.054 | 0.439 | -0.020       | 0.067 | 0.768 | 0.238            | 0.081 | 0.003 |
| R_ASIAN                  | 0.122       | 0.016 | 0.000 | 0.124        | 0.018 | 0.000 | 0.123            | 0.036 | 0.001 |
| R_HISPANIC               | -0.058      | 0.012 | 0.000 | -0.036       | 0.014 | 0.010 | -0.096           | 0.021 | 0.000 |
| R_HI_PACIF               | -0.112      | 0.094 | 0.233 | -0.094       | 0.099 | 0.340 | -0.137           | 0.226 | 0.544 |
| R_TWO_RACE               | -0.037      | 0.020 | 0.056 | -0.023       | 0.023 | 0.312 | -0.069           | 0.037 | 0.062 |
| COURSESCI                | 0.058       | 0.034 | 0.089 |              |       |       |                  |       |       |
| COURSEMATH               | -0.023      | 0.026 | 0.361 |              |       |       |                  |       |       |
| <i>n</i>                 |             | 23726 |       |              | 15845 |       |                  | 7881  |       |
| <i>k</i>                 |             | 1046  |       |              | 691   |       |                  | 356   |       |

Table 5: Educational Expectations and Mathematics Self-Efficacy, by Demographic Group

|                   | Educational Expectations |         |              |       |       |      |        |        |               | Mathematics Self-Efficacy |             |
|-------------------|--------------------------|---------|--------------|-------|-------|------|--------|--------|---------------|---------------------------|-------------|
|                   | Less than HS             | HS Grad | Some College | Cert. | Assoc | Bach | Master | Doctor | Bach or Above | Scale Mean                | Effect Size |
| Race/Ethnicity    |                          |         |              |       |       |      |        |        |               |                           |             |
| AA_Black          | 0.3                      | 1.8     | 2.1          | 2.1   | 8.8   | 35.1 | 28.9   | 20.9   | 84.9          | 3.38                      | -0.05       |
| Am_Indian         | 0.0                      | 0.0     | 0.0          | 3.1   | 12.3  | 52.3 | 13.9   | 18.5   | 84.6          | 3.58                      | 0.19        |
| Asian             | 0.2                      | 1.2     | 0.9          | 1.1   | 5.6   | 40.0 | 29.5   | 21.6   | 91.1          | 3.52                      | 0.11        |
| Hispanic          | 0.2                      | 2.3     | 2.0          | 3.4   | 10.7  | 40.1 | 26.3   | 15.0   | 81.3          | 3.38                      | -0.05       |
| Native_HI_Pacific | 0.0                      | 0.0     | 0.0          | 0.0   | 0.0   | 51.7 | 24.1   | 24.1   | 100.0         | 3.39                      | -0.04       |
| Two or more races | 0.0                      | 1.7     | 1.4          | 2.5   | 7.3   | 42.4 | 27.6   | 17.2   | 87.1          | 3.51                      | 0.10        |
| White             | 0.1                      | 1.1     | 1.1          | 1.5   | 5.5   | 47.6 | 27.6   | 15.6   | 90.8          | 3.49                      | 0.08        |
| First-Gen Student |                          |         |              |       |       |      |        |        |               |                           |             |
| No                | 0.1                      | 1.1     | 1.0          | 1.4   | 5.4   | 42.8 | 30.2   | 18.1   | 91.1          | 3.48                      | 0.07        |
| Yes               | 0.3                      | 2.6     | 2.3          | 3.9   | 12.1  | 41.3 | 23.7   | 13.8   | 78.8          | 3.36                      | -0.07       |
| Total             | 0.2                      | 1.9     | 1.7          | 2.6   | 8.7   | 42.1 | 27.0   | 16.0   | 85.0          | 3.42                      | 0.00        |