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Interplay of Motivational Beliefs and Self-Regulation with Achievement Across Economic Risk

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Abstract

We examined the additive associations of two motivational beliefs (growth mindset and academic self-efficacy) and self-regulation with mathematics and English Language Arts (ELA) scores, as well as the interplay of students' _beliefs and self-regulation skills, controlling for previous test scores. We tested whether these pathways differed across three mutually exclusive levels of economic risk: (1) low-risk students; (2) students receiving free and reduced price meals (FRPM); and (3) students identified as homeless and highly-mobile (HHM). Our results showed that motivational beliefs and self-regulation skills interact to promote academic achievement. Greater levels of growth mindset were related to higher academic achievement only for HHM students with higher levels of self-regulation.

Interplay of Motivational Beliefs and Self-Regulation with Achievement Across Economic Risk

A large body of research shows that motivational beliefs and self-regulation each contribute to academic achievement (Claro & Loeb, 2019b; Multon et al., 1991; West, et al., 2018). However, previous research predicting academic achievement from motivational beliefs (e.g., self-efficacy, growth mindset; Bandura, 1997; Dweck, 2006) and self-regulation has examined each of these predictors in isolation from each other (Dweck, 2006; Honicke & Broadbent, 2016; Jacob & Parkinson, 2015). As a result, we know little about the additive and interactive contributions of motivational beliefs and self-regulation to educational outcomes. Further, although previous research has documented socioeconomic disparities in student self-regulation (Duncan & Magnuson, 2011; Finch & Obradović, 2017b; Lawson et al., 2014; Rybski & Israel, 2019), we do not know whether the additive and interactive contributions of motivational beliefs and self-regulation to educational outcomes vary for students facing different contexts of economic risk. By examining how motivational beliefs and self-regulation contribute to achievement across levels of economic risk, we can move towards identifying how best to support academic success of students who experience more economic risks.

Leveraging data from the California Office to Reform Education (CORE) socioemotional learning survey (West et al., 2018), we test these processes in a large, representative sample of fourth through eighth grade students attending an urban school district. Specifically, we test how two motivational beliefs (growth mindset, and self-efficacy) and self-regulation skills additively and interactively relate to students' mathematics and English language arts (ELA) achievement and improvement. We examine whether these associations differ across three mutually exclusive levels of economic risk: (1) low-risk students; (2) students receiving free and reduced price meals (FRPM); and (3) students identified as homeless and highly-mobile (HHM).

Motivational Beliefs, Self-Regulation, and Academic Success

Recent legislative changes in the United States have made it easier to study motivational beliefs and self-regulation in large, representative samples. The Every Student Succeeds Act (2015) requires school districts to provide measures of accountability that go beyond students' performance on standardized achievement tests and graduation rates. Because robust evidence shows that motivational beliefs and self-regulation relate to students' achievement (Bandura, 1997; Blair & Raver, 2015; Dweck, 2006; Paunesku et al., 2015; Sisk et al., 2018), the California Office to Reform Education (CORE) districts adopted district-wide measures of motivational beliefs and self-regulation as part of their school improvement and accountability initiatives (West et al., 2018). Since the 2015–2016 school year, CORE districts have administered a comprehensive socioemotional learning and school climate survey to students in fourth grade and above. In this study, we focus on measures of motivational beliefs and skills with direct implications for academic achievement: growth mindset, self-efficacy, and self-regulation (Marsh et al., 2018).

Growth Mindset

Growth mindset is the motivational belief that, with effort, intelligence can be increased. It stands in contrast to fixed mindset, which is the belief that intelligence cannot be changed (Dweck, 2006). Growth mindset is associated with the motivation to seek out challenges (Nussbaum & Dweck, 2008) and to restrategize rather than to give up in the face of setbacks (Cain & Dweck, 1995). Previous cross-sectional analyses of the CORE survey data have found positive relations between growth mindset and academic performance in grades 4-12 (Claro &

Loeb, 2019b; West et al., 2018). In addition, a large meta-analysis revealed a weak, positive association between the measures of growth mindset and academic achievement (Sisk et al., 2018).

Self-Efficacy

Self-efficacy is the motivational belief that one is capable of accomplishing one's goals. According to Bandura's (1977; 1982) theoretical framework, efficacy expectations influence behavioral responses to difficulties, such as effort and persistence to overcome challenges. Self-efficacy is positively associated with grades (Honicke & Broadbent, 2016; Multon et al., 1991) from early elementary school through high school (Alivernini & Lucidi, 2011; Bandura et al., 1996; Pajares & Graham, 1999; West et al., 2018). Middle schoolers' self-efficacy also relates to a positive change in mathematics grades (Meece et al., 1990). Previous cross-sectional analyses of the CORE survey data have found positive relations between self-efficacy and academic performance in grades 4–12 (West et al., 2018), and a recent working paper using CORE survey data showed that a one-year change in self-efficacy is positively associated with a one-year change in academic performance in grades 3–8 (Kanopka et al., 2020).

Self-Regulation

Self-regulated students set goals for themselves, self-monitor, evaluate their progress, and change course accordingly, which are essential processes for learning (Zimmerman, 2000). Aspects of self-regulation such as executive functions, self-control, and effortful control are associated with academic skills across all grade levels, from preschool through high school (Blair & Raver, 2015; Duckworth & Seligman, 2005; Latzman et al., 2010; Iyer et al., 2010). Self-regulation skills on the CORE survey relate to state standardized mathematics and ELA scores among third–eighth graders (West et al., 2018). In large panel studies, self-regulation has been associated with growth in academic skills between prekindergarten and early elementary school (Blair et al., 2015; Fuhs et al., 2015) and across Grades 6–9 (Samuels et al., 2016).

Additive and Interactive Contributions of Motivational Beliefs and Self-Regulation

To better understand the importance of motivational beliefs and self-regulation skills for educational success, researchers need to identify the additive and interactive contributions of beliefs and skills for academic performance and change over time. According to the theory of self-regulated learning, motivational beliefs and self-regulation each contribute to academic learning bi-directionally such that motivation enhances self-regulation and self-regulation enhances motivation (Corno, 2008; Schunk & Zimmerman, 2012). Although most studies of motivational beliefs and self-regulation skills focus on a single domain, a few studies have examined additive contributions of skills and beliefs. Teacher-reported motivation predicted reading scores while controlling for teacher-reported self-regulation in a sample of 127 5- to 8-year-olds (Howse et al., 2003). In contrast, in a sample of 173 seventh graders, self-efficacy was significantly correlated with ELA achievement, but this association was not robust to controlling for self-regulation (Pintrich & de Groot, 1990). A recent working paper showed that student report of growth mindset, self-efficacy, self-regulation, and social awareness on the CORE survey uniquely related to academic improvement in math, and all except self-efficacy were uniquely linked to improvement in ELA in fourth- through seventh-graders (Claro & Loeb, 2019a). The sample sizes in most of these studies is small, and none of these studies examined differences in these relations across groups differentiated by socioeconomic risk. More work with larger sample sizes testing additive effects of beliefs and skills on academic performance and change over time across subgroups is needed so we can understand how beliefs and skills function for students in school.

The interplay among motivational beliefs and self-regulation skills is rarely studied, but a few studies offer initial evidence of potential interactive effects. In third through fifth graders, students' performance on executive function tasks and student report of the motivational belief of challenge preference interactively related to teacher report of assertive classroom behaviors (Finch & Obradović, 2017). Undergraduate motivational beliefs of enjoyment and pride in trigonometry interacted with self-regulation in relation to final course grades (Villavicencio & Bernardo, 2013). Inconsistent results across studies of the relation between beliefs and academic performance may be evidence of unexplored interactive effects with self-regulation skills (Sisk et al., 2018). While growth mindset and self-efficacy beliefs are often associated with positive academic outcomes (Claro & Loeb, 2019b; Honicke & Broadbent, 2016; Multon et al., 1991; West, et al., 2018), their effectiveness may vary as a function of students' ability to act upon those beliefs, as indexed by their self-regulation skills. Examining how self-regulation skills moderate relations between beliefs and academic outcomes may improve interventions designed to support academic achievement through beliefs and skills. Both motivational beliefs and self-regulation are important for academic achievement, but we do not yet know how each contributes to learning additively and interactively.

Motivational Beliefs and Self-Regulation in Contexts of Socioeconomic Risk

Students attending U.S. public schools vary widely in the economic resources they experience outside of school, and these resource disparities are reflected in academic disparities in math and ELA scores (Reardon & Portilla, 2016; Reardon, 2011). Students living in stressful or unstable environments may rely on their internal skills and beliefs for academic achievement more than students living in more physically supportive environments, where internal skills and beliefs are less consequential. If this is the case, then we would expect interventions on internal skills and beliefs to have stronger effects for more disadvantaged students. In fact, a study comparing Chilean tenth graders across income deciles showed that the relation between growth mindset and academic achievement was stronger for students who face higher levels of economic risk (Claro et al., 2016). Experimental studies of motivational belief and self-regulation interventions often find the strongest impacts on disadvantaged students' skills and beliefs (Diamond & Ling, 2016; Paunesku et al., 2015; Sisk et al., 2018), though many related studies do not differentiate findings across economic risk groups (Durlak et al., 2011). This indicates that the relation between the interaction of motivational beliefs and self-regulation and academic achievement may differ for students who face different levels of economic risk, and descriptive work examining this relation could inform future intervention efforts.

To address disparities in educational opportunities and outcomes associated with students' exposure to economic risk, U.S. federal policies mandate that school districts identify students who qualify for FRPM based on their family income (Richard B. Russell National School Lunch Act, 1946) and students who lack stable housing (McKinney-Vento Homeless Assistance Act, 2002). These indices represent a gradient of economic risk that can be used to understand whether motivational beliefs and self-regulation are similarly relevant for academic achievement of students exposed to different levels of risk.

In addition to challenges faced by FRPM students, HHM students' unstable housing status presents additional risks. Compared to their housed peers living in poverty, homeless teenagers reported more negligence and caregiver instability (Kurtz et al., 1991); more problems with drug use, mental health, crime, and schooling (Votta & Manion, 2004); and more violence and sexual assault (Kipke et al., 1997). In school, HHM students are more likely than their low-income, housed peers to experience frequent school changes (Cunningham et al., 2010), chronic absence from school (Low et al., 2017), repeating grades (Masten et al., 1993), lower reading and mathematics proficiency in elementary school (Obradović et al., 2009) and 3rd–8th grade (Cutuli et al., 2013; Herbers et al., 2012), and ultimately lower graduation rates (Low et al., 2017).

At the same time, there is substantial heterogeneity in educational outcomes among students who are identified by schools as qualifying for FRPM or having HHM status (Obradović et al., 2009; Spitzley, 2020). Research with smaller, selective samples of 4- to 6-year-olds has shown that executive functions, an aspect of self-regulation, promote academic resilience among high-risk groups (Masten et al., 2012; Obradović, 2010). Given the strong negative impact that HHM status can have on developmental outcomes (D'Sa et al., 2020), there is a need to identify additional factors that can promote academic success among these students (Cutuli & Herbers, 2014; Masten et al., 2014). By identifying differences in how motivational beliefs and self-regulation relate to academic achievement in HHM students and low-income, housed students, as well as their low-risk peers, we can reduce academic achievement gaps by improving programs that promote these beliefs and skills in economically diverse student populations.

The Present Investigation

Important research gaps remain as to how motivational beliefs and self-regulation function additively and in concert with one another to contribute to academic performance and change in performance, as well as how these processes differ for students facing different levels of socioeconomic risk. Filling in these gaps will inform equity-oriented intervention design. This study leverages the CORE survey to address these gaps by examining additive and interactive effects of the motivational beliefs of growth mindset and self-efficacy with self-regulation on academic achievement in a large, representative sample of fourth through eighth grade students attending an urban public school district. Further, we examined the effects on students' performance on state-mandated standardized mathematics and ELA achievement tests as well as on the longitudinal one-year change in students' academic achievement by accounting for students' previous test performance.

We hypothesized that each of the domains of growth mindset, self-efficacy, and self-regulation would uniquely relate to academic performance when included in the same model. We hypothesized that each of the domains would also uniquely relate to a one-year change in academic performance, albeit to a lesser degree given strong longitudinal stability of students' test scores. We focused our investigation of interactive effects on whether students' self-regulation skills moderated the association between students' motivational beliefs (growth mindset and self-efficacy) and academic outcomes. We hypothesized that higher levels of self-regulation would enhance the contributions of students' growth mindset and self-efficacy to academic performance and change in academic performance over time.

In order to better understand how motivational beliefs and self-regulation function across groups of students exposed to different levels of economic risk, we examined these processes in three mutually exclusive groups: (1) low-risk students who are neither receiving FRPM nor identified as HHM; (2) non-HHM students receiving FRPM; and (3) HHM students. Given the research showing stronger relations between the motivational belief of growth mindset and academic achievement for more disadvantaged students (Claro et al., 2016), we hypothesized that the strengths of the associations between each domain and academic outcome would increase as economic risk increased across the groups.

Method

Participants

The sample for this study (N = 17,029) consisted of all of the students in one of the large, urban CORE school districts who had taken the CORE survey (West et al., 2018) in Grades 4–8 during the 2015–2016 school year. Student grade, demographics, attendance, and standardized test scores for the 2014–2015 and 2015–2016 school years were obtained from school district administrative records.

Based on HHM identification policies required by the McKinney-Vento Act (2002), students were identified by the school district as HHM if their nighttime residence status was unstable or inadequate, which includes students who were unsheltered (such as sleeping in a bus station or in a tent); sheltered but doubled up in a single-family home; residing in a motel or hotel; or migratory. The analytic sample included 7,144 non-homeless students who did not receive FRPM during the 2015–2016 school year, 9,099 non-homeless students who received FRPM, and 772 students who were identified by the school district as HHM. Of the students in the sample, 49.3% were female. By race and ethnicity, 7.3% were Black, 44.3% Asian/Pacific-Islander, 26.3% Hispanic, 17.2% white, and 4.8% another race or ethnicity. See Table 1 for a description of students across groups.

Students who were missing all CORE survey data (n = 2,889) were not included in the analytic sample. Non-respondents were more likely than respondents to be male (p = .046, d = 0.07); Black (p < .001, d = 0.25), Latinx (p = .002, d = 0.10), or white (p = .046, d = 0.06); have HHM status (p = .004, d = 0.16); lack FRPM status (p = .021, d = 0.16); and have lower attendance (p < .001, d = 0.75) and lower standardized test scores in mathematics and ELA (ps < .001, ds range from 0.24–0.34).

Of the CORE survey respondents, 894 (5.25%) did not complete the 2014–2015 mathematics assessment and 1075 (6.31%) did not complete ELA assessments. 375 (2.20%) and 478 (2.81%) did not complete the 2015–2016 mathematics and ELA assessments, respectively. Of students who completed at least one CORE Survey response, 5 (0.03%) did not fill out the self-regulation scale, 42 (0.25%) did not fill out the growth mindset scale, and 47 (0.28%) did not fill out the academic self-efficacy scale. One person (0.01%) was missing an attendance rate. No other study variables were missing data. In our analyses, we used full information maximum likelihood (FIML) in Mplus 7.4 to account for missing data (Muthén & Muthén, 1998-2015).

Measures

Academic Performance

The district administered the Smarter Balanced Assessment Consortium (SBAC, 2016) standardized tests based on the Common Core State Standards in mathematics and ELA to Grades 4–8 in the spring of 2015 and 2016. The reliability of the SBAC was excellent. Depending on the grade and year, ρ ranged from .91–.93 for ELA and from .90–.94 for math (California Department of Education, 2017).

Motivational Beliefs and Self-Regulation Skills

Two motivational beliefs—growth mindset and academic self-efficacy— and self-regulation were assessed using student report on the CORE survey (West et al., 2018). *Growth mindset* was assessed with a four-item Likert scale (e.g., "My intelligence is something that I can't change very much") based on mindset theory (Dweck, 2006). Response choices ranged from 1 (Not at All True) to 5 (Completely True). *Academic self-efficacy* was measured with a four-item Likert scale (e.g., "I can master the hardest topics in my class") that was based on Bandura (1997) and created by Transforming Education (2016). Response choices ranged from 1

(Not at All Confident) to 5 (Completely Confident). *Self-regulation* was assessed using a nine-item Likert scale (e.g., "I stay focused when working independently") adapted from Patrick and Duckworth's (2013) and Park et al. (2017). Response choices ranged from 1 (Almost Never) to 5 (Almost Always).

The CORE survey domains have been field-tested for reliability and validity for use in research (West et al., 2018). Further, the measures were assessed for their validity in terms of their content and structure. Analyses showed that the questions captured the underlying constructs and that each scale was unidimensional (West et al., 2018). In our sample, internal reliability (Cronbach's alpha) was .65 for growth mindset, .77 for academic self-efficacy, and .84 for self-regulation. See Table 1 for internal reliabilities of these scales in each of the three analytic sub-samples.

Covariates

All models controlled for student demographics, which were reported by parents. Demographic covariates included race/ethnicity (Black, Latinx, Asian/Pacific Islander, white and other), and gender (male, female). Models also controlled for attendance rate. See Table 1 for a comparison of covariates across economic risk groups.

Analysis Plan

Main analyses consisted of a hierarchical multi-group path analysis. Multi-group analysis allowed us to make comparisons across the three economic risk groups. All models were fully saturated and therefore had perfect fit. We report the change in R^2 as a measure of effect size. In all models, we included clustering at the school level to account for the nesting of students within schools (Raudenbush & Bryk, 2002). All analyses were carried out using robust standard errors (MLR), clustered at the school level, in Mplus 7.4 (Muthén & Muthén, 1998–2015).

First, we compared the additive contributions of growth mindset, self-efficacy, and self-regulation across the three economic risk groups. In our baseline model (Model 1), we controlled for the contribution of demographic covariates, grade level, and attendance rate. In Model 2, we tested the main effects of students' growth mindset, academic self-efficacy, and self-regulation. Next, we examined how self-regulation skills moderated the relations of two motivational beliefs with academic performance. In Models 3A, we tested a two-way interaction between students' self-regulation and growth mindset. In Model 3B, we tested a two-way interaction between self-regulation and academic self-efficacy. We then repeated all of these analyses, controlling for earlier academic achievement test scores. For each of the predictors in Model 2 and Models 3A/3B, we tested equivalence of the coefficients across each pair of risk groups using chi-square difference tests.

All models controlled for student race and ethnicity, sex, and attendance rate because these variables have been shown to relate to both socioeconomic status and academic performance (Gottfried, 2014; Reardon et al., 2014; Reardon, 2011; Reardon et al., 2019). All models control for grade level in school year 2015–2016 to account for different developmental ages of students in the sample (McKown, 2017).

Results

Descriptive Statistics

Means and *SDs* for demographic covariates, motivational beliefs and self-regulation measures, and standardized test scores for each of the groups are described in Table 1. This table includes the results of Wald tests indicating significant mean level differences in demographics, motivational beliefs, self-regulation, and standardized test scores across the groups, along with effect sizes of these differences. Consistent with the literature on economic disparities in socioemotional skills and academic performance (Duncan & Magnuson, 2011; Reardon, 2011), students from more disadvantaged groups had lower average levels of motivational beliefs and self-regulation as well as mathematics and ELA scores.

Bivariate Correlations

Table 2 presents bivariate correlations among motivational beliefs and self-regulation and academic assessments split by economic risk groups. Within each risk group, student-reported motivational beliefs and self-regulation were positively inter-correlated. The correlations among beliefs and skills were largest in the low-risk group and smallest in the HHM group. In each group, the largest correlations were between self-regulation and academic self-efficacy (rs ranged from .48–.52, ps < .001). Self-regulation was also correlated with growth mindset (rs ranged from .11–.30, ps = .002 or $p < .001$), and growth mindset was correlated with academic self-efficacy (rs ranged from .19–.41, ps < .001). Each of the student-reported belief and skill domains was positively correlated with 2015 and 2016 standardized test scores in mathematics and ELA in each group (rs ranged from .20–.41, ps < .001).

Multi-group Structural Equation Models

Direct Effects of Socioemotional Skills and Beliefs

Table 3 presents the results of Model 1 (baseline model) that explained approximately one-fifth to one-third of the variance in performance in mathematics (total variance explained ranged from 21.8–36.5%) and ELA (total variance explained ranged from 21.6–31.5%).

In Model 2, all three belief and skill domains uniquely predicted both mathematics and ELA scores regardless of risk group status (self-regulation: βs ranged from 0.13–0.21, ps < .001;

growth mindset: βs ranged from 0.19–0.23, ps < .001; academic self-efficacy: βs ranged from 0.06–0.17, ps $\leq$ .015). Inclusion of motivational beliefs and self-regulation explained an additional 11.6–14.5% of variance, with the largest boost in explanatory power among HHM students. Total variance explained ranged from 36.3–48.8%.

The associations of growth mindset with mathematics and ELA scores were similar across three groups (Wald test ps ranged from 0.109–0.702). The associations of academic self-efficacy with mathematics and ELA scores were stronger for low-risk students than they were for both other groups (Wald test ps < .001). The associations of self-regulation with mathematics and ELA scores were stronger in in the FRPM group than in the low-risk group (Wald test ps = .003 and .006, respectively).

Longitudinal models. Growth mindset uniquely predicted a one-year change in both mathematics and ELA scores regardless of risk group status (βs ranged from .05–.10, ps ranged from < .001 to .024). The association of growth mindset with a one-year change in mathematics scores was stronger for HHM students than FRPM or low-risk students (Wald test ps = .022 and .012, respectively), whereas the association of growth mindset with a one-year change in ELA scores did not differ across groups (Wald test ps ranged from .166–.956).

Academic self-efficacy was only significantly associated with a one-year change in mathematics for low-risk students (β = 0.027, p = .002) and FRPM students (β = 0.024, p = .004), and with a one-year change in ELA for low-risk students (β = 0.020, p = .018). Associations of academic self-efficacy with one-year changes in academic scores did not differ across groups (Wald test ps ranged from .167–.996). Inclusion of motivational beliefs and self-regulation explained an additional 0.7–2.3% of variance, with the largest boost in explanatory power among HHM students.

After controlling for previous test scores, self-regulation uniquely predicted both mathematics and ELA scores regardless of risk group status (βs ranged from .05–.09, *p*s ranged from < .001 to .002). The association of self-regulation with a one-year change in ELA scores was stronger for FRPM students than low-risk students ($p = .012$). The associations between self-regulation and a change in mathematics scores did not differ across groups (Wald test *p*s ranged from .110–.812).

Interactive Effects of Self-regulation and Growth Mindset

In Model 3A, self-regulation positively moderated the relation of growth mindset with mathematics and ELA scores for all groups (βs ranged from 0.04–0.12, *p*s < .001). Because of the large sample size, interactions can be statistically significant without meaningfully contributing to prediction. We report on interactions only if they are both statistically significant and they increase the model R^2 by more than 0.1%. Adding the interaction term between self-regulation and growth mindset increased the model R^2 by 0.2% and 1.5% for low-risk students, 0.5% and 0.5% for FRPM students, and 1.9% and 2.3% for HHM students in mathematics and ELA, respectively.

As illustrated in Figure 1, the positive association of growth mindset and academic achievement was stronger for students who also reported higher levels of self-regulation than for students who reported lower levels of self-regulation. This was true across all three groups.

Wald tests showed that the interaction coefficients were significantly stronger for the HHM group when compared to the low-risk group (*p*s = .002 and .004) and the FRPM group (*p*s = .045 and .039), but not statistically different between the low-risk and FRPM groups (*p*s = .119 and .053). Among HHM students who reported higher levels of self-regulation, the association of growth mindset with mathematics achievement was stronger compared to students in the FRPM and low-risk groups (*p*s = .004 and .005). Among HHM students who reported lower levels of self-regulation, the association of growth mindset with mathematics and ELA achievement was not statistically significant, whereas analogous simple slopes were significant for FRPM and low-risk students.

Longitudinal models. After controlling for previous achievement, self-regulation moderated the relation of growth mindset with mathematics and ELA scores for FRPM students (βs = .02, *p*s = .016 and .008) and HHM students (βs = .06 and .05, *p*s < .001). However, addition of the interaction term between self-regulation and growth mindset significantly explained additional variance only in the HHM group, by 0.5% and 0.4% on mathematics and ELA scores, respectively. Thus, we interpreted the significant interaction term only in the HHM group. The association of growth mindset and a one-year change in academic achievement was only statistically significant for HHM students who also reported higher levels of self-regulation but not significant for HHM students who reported lower levels of self-regulation.

Interactive Effects Self-regulation and Academic Self-Efficacy

In Model 3B, self-regulation moderated the relation of academic self-efficacy with mathematics and ELA scores in the FRPM group (βs = .02, *p*s = .003 and .032) and HHM group (βs = .08, *p*s = .001 and < .001). However, addition of the interaction term between self-regulation and academic self-efficacy significantly explained additional variance only in the HHM group, by 1.0% and 1.3% on mathematics and ELA scores, respectively. Thus, we interpreted the significant interaction term only in the HHM group.

As illustrated in Figure 1, the associations between academic self-efficacy and academic achievement in mathematics and ELA were significant for HHM students who reported higher levels of self-regulation (βs = .154 and .153, ps <.001), but they were not significant for HHM students who reported lower levels of self-regulation.

Longitudinal Models. After controlling for previous achievement, the addition of the interaction term between self-regulation and academic self-efficacy no longer fulfilled our reporting criteria of being statistically significant and increasing the R^2 by more than .1% for any risk group, so we did not interpret the interaction effect.

Discussion

This study revealed how motivational beliefs and self-regulation additively and interactively relate to overall levels of academic achievement and longitudinal change in academic achievement across levels of economic risk. Corroborating recent working papers (Claro & Loeb, 2019a; Kanopka et al., 2020), we showed that growth mindset, self-efficacy, and self-regulation were uniquely associated with performance and change in performance on standardized mathematics and ELA achievement tests. This was the case for students across three levels of economic risk: low-risk students who do not qualify for FRPM and are not identified as HHM students, students receiving FRPM, and HHM students. We extended this literature by showing that the strength of these associations differed across levels of economic risk. First, self-efficacy emerged as relating uniquely to achievement and longitudinal change in achievement for low-risk students. Second, self-regulation emerged as having a stronger relation with both ELA and mathematics achievement and longitudinal change in ELA achievement in the FRPM group when compared to the low-risk group. Third, growth mindset had a stronger association with a one-year change in mathematics test scores for HHM students when compared to the other two groups. Further, across all three risk groups, the associations of growth mindset or self-efficacy with academic performance were moderated by students' self regulation: All students benefited more from high levels of growth mindset or self-efficacy beliefs when they also reported high levels of self-regulation. However, when controls for earlier achievement were added to the models, high growth mindset promoted academic improvement only for HHM students who also had high levels of self-regulation.

Self-efficacy emerged as having a unique association with achievement and longitudinal change in achievement for low-risk students, corroborating previous work showing the association between self-efficacy and grades or test scores (Alivernini & Lucidi, 2011; Honicke & Broadbent, 2016; West et al., 2018). Self-efficacy captures the belief that one is able to perform academically, which can reflect students' accurate perceptions of their own abilities, so it is unsurprising that students who believe they can, for instance, "master hard topics" or "earn an A" do perform better on standardized tests than students who do not (West et al., 2018). However, self-efficacy made little or no unique additive or interactive contribution to longitudinal change in ELA or mathematics for students facing economic or housing adversity. These findings indicate that even among students who strongly believe in themselves, there are still barriers to learning for students facing economic risks. These heterogeneous outcomes may explain low and null associations of self-efficacy with academic performance in recent working papers using CORE data (Claro & Loeb, 2019a; Kanopka et al., 2020).

Self-regulation has been linked to academic performance and change in performance, likely because it captures skills universally needed for school-based learning such as coming to class prepared, focusing on work, and following directions (Blair & Raver, 2015; Samuels et al., 2016; West et al., 2018). Corroborating this line of work, self-regulation skills were positively associated with performance and a one-year change in performance for all three economic risk groups. These findings extend previous research indicating self-regulation as a promotive factor for HHM students (Masten et al., 2012; Obradović, 2010), by examining the relative strength of the interplay of motivational beliefs and self-regulation across risk groups. We extend these results to show that self-regulation had stronger associations with ELA and mathematics achievement and longitudinal change in ELA achievement for the FRPM group than the low-risk group. These results may indicate that students facing instability or stress related to greater economic risk lean more heavily on their internal resources in order to engage in academic learning.

Growth mindset is believed to be especially important for students facing adversity because of its relation to motivation and perseverance in the face of challenges (Cain & Dweck, 1995). Indeed, previous research shows stronger benefits of growth mindset for the most disadvantaged students (Paunesku et al., 2015). In line with this, our results show that growth mindset had a stronger association with a one-year change in mathematics test scores for HHM students than for the other groups. However, our results extend this further to show that HHM students with low self-regulation see no association between growth mindset and academic performance. Many HHM students lack sufficient external supports for learning. As a result, HHM students must rely heavily on their own self-regulation skills for the focus of their attention and organization of their studies. In the absence of external support, believing in their ability to grow may not be enough to overcome chaos and instability of their situations, especially without strong self-regulation skills.

Although interaction effects only explained a small percent of variance in academic achievement for each economic risk group, the combination of self-regulation and growth mindset can have meaningful impact on HHM students. Among HHM students with high growth mindset, the differences in mathematics and ELA scores between those with high self-regulation and low self-regulation are .60 and .53 *SD*s, respectively. National norms indicate students in grades 3–8 improve on standardized mathematics and ELA test scores by .25–.56 *SD*s in one year (Hill et al., 2008; Smarter Balanced Assessment Consortium, 2018). This means that among HHM students with high growth mindset, those with high self-regulation skills are, on average, between one and two years ahead in academic skills.

Knowing there are economic gaps in academic performance, these results show that levels of motivational beliefs and self-regulation may have striking implications for equity as late as middle school. Together, our results suggest that economic gaps in growth mindset, self-efficacy, and self-regulation may, in part, explain the size of economic gaps in mathematics and ELA scores between risk groups. We found that economic gaps were smallest among students with a combination of either high growth mindset or self-efficacy and high self-regulation. However, because motivational beliefs and self-regulation interact to promote achievement, especially for higher-risk students, economic gaps may be wider among low-risk and higher-risk students who have high levels of motivational beliefs and low levels of self-regulation, or vice versa.

The natural follow-up question is whether or not this link is causal and whether interventions can change students' academic trajectories, especially for those who are low-income or HHM. Our results show that self-regulation explains the most variance in outcomes for high-risk students, so targeting self-regulation could benefit all students while also narrowing the economic gap. Further, our results suggest that complementing growth mindset and self-efficacy interventions with programs that also target self-regulation may improve both overall performance and equity. Family income has been related to aspects of motivational beliefs and self-regulation in several studies (Finch & Obradović, 2017; Liew et al., 2008; Raver et al., 2013). Socioeconomic context can affect the support and motivation a student has for academic learning via competing stressors, incentives, and distractions (Eccles & Wigfield, 2002). Improving the motivational beliefs and self-regulation of disadvantaged students has been shown to be an effective and relatively inexpensive lever for improving academic performance (Paunesku et al., 2015; Schmitt et al., 2015).

Our results also point to housing as a target for intervention. Even HHM students with the highest levels of motivational beliefs and self-regulation still lag in mathematics and ELA behind low-income students who have stable, adequate housing. Disadvantages in motivational beliefs and self-regulation originate in disparities in opportunities available to students (Duncan & Magnuson, 2011). It may be that adversity itself is the best target of intervention, and that changing a student's risk status will lead to improved motivational beliefs, self-regulation, and academic outcomes in the long run. The most important levers for improving the outcomes of students who are disadvantaged may be policies that systemically relieve adversities through increasing family income (Dahl & Lochner, 2012) and providing stable housing (Chetty et al., 2016). Given our results showing that motivational beliefs and self-regulation are lower in low-income and HHM students and that these skills and beliefs are related to a one-year change in achievement, future work should examine whether motivational beliefs and self-regulation mediate the relation between housing supports and academic achievement. Improving external supports to reduce the burdens of low socioeconomic and HHM status should continue to be researched and pursued as schools seek to improve motivational beliefs, self-regulation, and academic skills for their students.

Strengths, Limitations, and Future Directions

In this study, we used reliable student-reported measures of motivational beliefs and self-regulation in a large, representative, district-wide sample of students. Our assessment strategy allowed us to draw generalizable conclusions as we compared how these beliefs and skills functioned differently across economic risk groups, including a large group of understudied, high-risk HHM students. Previous work on aspects of self-regulation in HHM students used small, select samples (Masten et al., 2012; Obradović, 2010), and the work that used large, administrative datasets did not measure motivational beliefs and self-regulation (Masten et al., 2008; Obradović et al., 2009). Our classification of low-risk students is limited by available administrative data (i.e., FRPM and HHM status) and does not reflect other sources of risk and adversity. On the other hand, the available administrative indicators of risk have been shown to correlate with unobservable structural, neighborhood, domestic, and health risks (e.g., Kipke et al., 1997; Kurtz et al., 1991; Reardon, 2011; Reardon & Portilla, 2016; Votta & Manion, 2004), and have been used in previous work to delineate a risk gradient (Masten et al., 2008; Obradović et al., 2009). For designing interventions, they have the policy-relevant advantage of being used in every public school district in the U.S. (McKinney-Vento Homeless Assistance Act, 2002; Richard B. Russell National School Lunch Act, 1946).

Although there is no single "best" measure of motivational beliefs and self-regulation, self-report questionnaires of these domains were the "most valid measure[s] for [our] intended purpose" (Duckworth & Yeager, 2015, p. 245). The survey we used was field tested for reliability and validity (West et al., 2018). It was not heavily weighted in high-stakes assessments of school improvement, so we have no reason to believe the student self-reports were biased due to pressures related to accountability (West et al., 2018). Direct assessment at this scale would have been costly and resource-intensive.

We used high-quality, reliable standardized academic outcomes across two time points, allowing us to control for prior achievement. Our research methods included a multi-group path analysis, which allowed us to make comparisons of path coefficients across groups. Our study builds on previous work linking changes in socioemotional learning to changes in academic performance and change over time (Durlak et al., 2011), but experimental studies will be needed to confirm that the interactions between motivational beliefs and self-regulation skills have causal impacts on academic achievement.

Our work suggests that practitioners and researchers should consider how motivational beliefs and self-regulation affect children differently across different levels of risk. Future work should also consider other belief and skill interactions that can reveal promotive and protective factors that contribute to resilience and success for HHM students and other students facing adversity. Another possible area for future work is to consider whether there may be bidirectional associations between motivational beliefs, self-regulation, and academic outcomes across different time points, such as a positive cascade (Masten & Cicchetti, 2010). Finally, researchers, policy-makers, and school leaders should consider how robust structural supports can decrease the necessity for HHM students to rely on their own motivational beliefs and self-regulation for academic success over and above their better-resourced peers.

Conclusion

Our results showed that motivational beliefs and self-regulation skills interact to promote academic achievement, and the strength of their associations with achievement differs across economic risk groups. The different patterns we see in terms of the magnitudes of associations for each domain highlight the need for work that further explores differences in how motivational beliefs and self-regulation uniquely contribute to positive change in academic achievement across the spectrum of economic risk. Our results imply that having strong positive beliefs in personal abilities or potential may be important for academic success, but to best impact students—especially the most disadvantaged students—these beliefs need to be accompanied by a strong skill set in self-regulation. This interaction may be one reason growth mindset interventions see such mixed results (Sisk et al., 2018; Yeager et al., 2019), as the impact of growth mindset on learning depends on the presence of self-regulation skills. If motivational beliefs and self-regulation skills are promoted in a way that benefits only low-risk students, achievement gaps can widen. Our findings suggest that interventions that target multiple skill and belief domains at once, fostering beliefs about the students' own abilities to handle challenges and giving students the self-regulation skills they need, may improve all students' academic outcomes while also increasing equity.

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Table 1

Descriptive Statistics by Economic Risk Group in Unimputed Analytic Sample

	Low-Risk				FRPM				HHM		
	Mean	*SD*	α	$d^{\dagger}$	Mean	*SD*	α	$d^{\ddagger}$	Mean	*SD*	α
Female	.50[a]	.50			.49[a]	.50			.49[a]	.50	
Asian	.43[a]	.50			.50[b]	.50			.21[c]	.41	
Black	.04[a]	.20			.09[b]	.28			.13[c]	.33	
Latinx	.14[a]	.34			.32[b]	.47			.59[c]	.49	
White	.32[a]	.47			.07[b]	.25			.05[b]	.21	
Other	.07[a]	.25			.03[b]	.16			.02[b]	.15	
Grade Level in 2016	5.81[a]	1.40		-0.20	5.88[b]	1.40		-0.09	5.96[b]	1.40	
Attendance Rate 2016	97.57[a]	2.92		0.05	97.39[b]	3.72		0.54	95.52[c]	5.52	
English 2015	2532.52[a]	98.14		0.64	2468.68[b]	101.19		0.31	2437.45[c]	93.02	
Mathematics 2015	2536.87[a]	97.49		0.55	2482.96[b]	101.53		0.44	2438.60[c]	92.17	
English 2016	2567.19[a]	99.25		0.64	2501.44[b]	103.94		0.39	2462.25[c]	91.34	
Mathematics 2016	257.36[a]	104.99		0.53	2509.47[b]	111.46		0.49	2459.00[c]	97.53	
Self-Regulation	4.20[a]	0.60	.84	0.34	3.98[b]	0.68	.85	0.25	3.81[c]	0.72	.84
Growth Mindset	3.89[a]	0.92	.72	0.37	3.54[b]	0.92	.68	0.12	3.43[c]	0.94	.65
Academic Self-Efficacy	3.78[a]	0.90	.87	0.32	3.49[b]	0.94	.85	0.18	3.32[c]	0.99	.85
N	7144				9099				779		

Note. Superscripts next to means indicate which covariates, assessment scores, motivational beliefs, or skills are significantly different across risk groups. In each row, means marked with different letters are significantly different from each other at the .05 level.

† Cohen's *d* of significant differences between Low-Risk and FRPM students.

‡ Cohen's *d* of significant differences between FRPM and HHM students.

Table 2

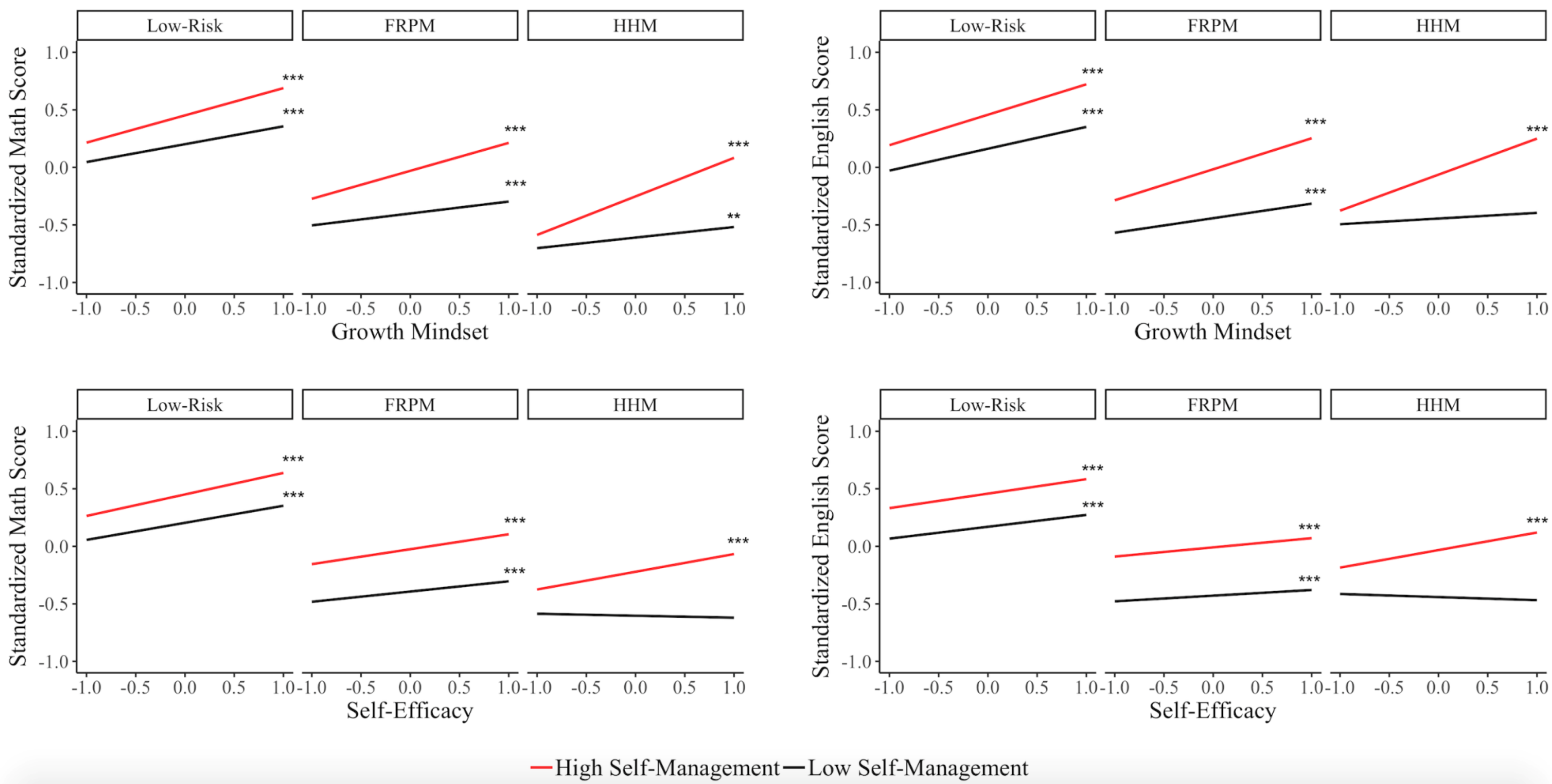
Bivariate Correlations by Economic Risk Group in Unimputed Analytic Sample

	SM	GM	SE	E15	M15	E16
	Low-Risk					
Growth Mindset	.30					
Academic Self-Efficacy	.52	.41				
English 2015	.33	.39	.33			
Math 2015	.31	.36	.31	.84		
English 2016	.37	.41	.37	.86	.80	
Math 2016	.35	.38	.35	.79	.89	.82
	FRPM					
	SM	GM	SE	E15	M15	E16
Growth Mindset	.18					
Academic Self-Efficacy	.49	.27				
English 2015	.35	.33	.22			
Math 2015	.35	.31	.25	.81		
English 2016	.39	.34	.24	.85	.80	
Math 2016	.39	.33	.27	.77	.88	.81
	HHM					
	SM	GM	SE	E15	M15	E16
Growth Mindset	.11					
Academic Self-Efficacy	.48	.19				
English 2015	.29	.31	.20			
Math 2015	.29	.31	.23	.76		
English 2016	.33	.31	.22	.79	.71	
Math 2016	.33	.35	.26	.71	.80	.74

Notes. Acronyms: SM = self-regulation. GM = growth mindset. SE = academic self-efficacy. E15 = ELA scores in 2015. M15 = Math scores in 2015. E16 = ELA scores in 2016. (*ps* < *.001*).

Figure 1

Simple-Slopes of Beliefs by Levels of Self-Regulation.



Note: Self-regulation moderates the association between beliefs and performance in mathematics and English Language Arts, especially for students facing greater risk. Stars indicate statistical significance of simple slopes: * $p < .01$ ** $p < .05$ *** $p < .001$.

Table 3

Results of Multi-Group Path Analyses of Self-Regulation and Motivation on Academic Performance Across Risk Groups

	Math 2016										English 2016									
	1	2			3A			3B			1	2			3A			3B		
Low-Risk		*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*		*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*
SM		.13	(.02)	.000	.13	(.02)	.000	.13	(.02)	.000		.16	(.02)	.000	.16	(.02)	.000	.16	(.02)	.000
GM		.20	(.01)	.000	.19	(.02)	.000	.20	(.01)	.000		.23	(.01)	.000	.22	(.01)	.000	.23	(.01)	.000
SE		.17	(.02)	.000	.17	(.02)	.000	.17	(.02)	.000		.12	(.01)	.000	.12	(.01)	.000	.12	(.01)	.000
SM x GM					.05	(.01)	.000								.04	(.01)	.001			
SM x SE								.02	(.01)	.050								.01	(.01)	.246
R^2	.298	.442			.444			.442			.279	.427			.442			.427		
FRPM																				
SM		.18	(.01)	.000	.19	(.01)	.000	.19	(.01)	.000		.21	(.01)	.000	.22	(.01)	.000	.21	(.01)	.000
GM		.19	(.01)	.000	.19	(.01)	.000	.19	(.01)	.000		.21	(.01)	.000	.21	(.01)	.000	.21	(.01)	.000
SE		.11	(.02)	.000	.11	(.01)	.000	.11	(.01)	.000		.06	(.01)	.000	.06	(.01)	.000	.07	(.01)	.000
SM x GM					.07	(.01)	.000								.07	(.01)	.000			
SM x SE								.02	(.01)	.003								.02	(.01)	.032
R^2	.365	.481			.486			.481			.315	.440			.445			.440		
HHM																				
SM		.16	(.030)	.000	.20	(.03)	.000	.20	(.03)	.000		.18	(.03)	.000	.21	(.03)	.000	.22	(.03)	.000
GM		.23	(.031)	.000	.26	(.03)	.000	.23	(.03)	.000		.20	(.03)	.000	.23	(.03)	.000	.20	(.03)	.000
SE		.07	(.027)	.015	.06	(.03)	.014	.10	(.03)	.001		.06	(.03)	.021	.06	(.03)	.024	.09	(.03)	.002
SM x GM					.11	(.02)	.000								.12	(.02)	.000			
SM x SE								.08	(.023)	.001								.08	(.02)	.000
R^2	.218	.363			.382			.373			.216	.353			.376			.366		

Notes. Low-risk students, $N = 7144$. Students receiving FRPM, $N = 9099$. Students identified as HHM, $N = 779$. All models control for gender, race and ethnicity, attendance rate, and grade level. Standard errors in parentheses are clustered at the school level.

Table 4

Results of Multi-Group Path Analyses of Self-Regulation and Motivation on a One-Year Change in Academic Performance Across Risk Groups

	Math 2016											
	1			2			3A			3B		
Low-Risk	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*
M/E 15	.86	(.01)	.000	.82	(.01)	.000	.81	(.01)	.000	.82	(.01)	.000
SM				.05	(.01)	.000	.05	(.01)	.000	.05	(.01)	.000
GM				.05	(.01)	.000	.05	(.01)	.000	.05	(.01)	.000
SE				.03	(.01)	.002	.03	(.01)	.002	.03	(.01)	.002
SM x GM							.01	(.01)	.105			
SM x SE										(.00)	(.01)	.761
R^2		.798			.805			.805			.805	
FRPM												
M/E 15	.82	(.01)	.000	.77	(.01)	.000	.77	(.01)	.000	.77	(.01)	.000
SM				.07	(.01)	.000	.07	(.01)	.000	.06	(.01)	.000
GM				.05	(.01)	.000	.05	(.01)	.000	.05	(.01)	.000
SE				.02	(.01)	.004	.02	(.01)	.004	.02	(.01)	.004
SM x GM							.02	(.01)	.016			
SM x SE										(.01)	(.01)	.419
R^2		.782			.790			.790			.790	
HHM												
M/E 15	.74	(.03)	.000	.68	(.03)	.000	.67	(.03)	.000	.67	(.03)	.000
SM				.07	(.02)	.002	.09	(.02)	.000	.08	(.03)	.001
GM				.10	(.02)	.000	.11	(.02)	.000	.10	(.02)	.000
SE				.02	(.02)	.191	.02	(.02)	.198	.03	(.02)	.082
SM x GM							.06	(.02)	.000			
SM x SE										.021	(.014)	.134
R^2		.649			.672			.677			.673	

	English 2016											
	1			2			3A			3B		
Low-Risk	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*	*ß*	*(se)*	*p*
M/E 15	.83	(.01)	.000	.78	(.01)	.000	.78	(.01)	.000	.78	(.01)	.000
SM				.06	(.01)	.000	.06	(.01)	.000	.06	(.01)	.000
GM				.07	(.01)	.000	.07	(.01)	.000	.07	(.01)	.000
SE				.02	(.01)	.018	.02	(.01)	.016	.02	(.01)	.018
SM x GM							.01	(.01)	.523			
SM x SE										-.01	(.01)	.460
R^2		.748			.759			.759			.759	
FRPM												
M/E 15	.81	(.01)	.000	.75	(.01)	.000	.75	(.01)	.000	.75	(.01)	.000
SM				.09	(.01)	.000	.09	(.01)	.000	.08	(.01)	.000
GM				.06	(.01)	.000	.06	(.01)	.000	.06	(.01)	.000
SE				.01	(.01)	.189	.01	(.01)	.202	.00	(.01)	.427
SM x GM							.02	(.01)	.008			
SM x SE										-.01	(.01)	.003
R^2		.744			.754			.755			.755	
HHM												
M/E 15	.73	(.03)	.000	.68	(.03)	.000	.66	(.03)	.000	.67	(.03)	.000
SM				.08	(.03)	.001	.10	(.03)	.000	.10	(.03)	.000
GM				.06	(.03)	.024	.07	(.03)	.005	.06	(.03)	.025
SE				.02	(.02)	.210	.02	(.02)	.227	.04	(.02)	.046
SM x GM							.05	(.01)	.000			
SM x SE										.029	(.02)	.054
R^2		.638			.654			.658			.656	

Notes. Sample sizes: Low-risk students, *N* = 7144. Students receiving FRPM, *N* = 9099. Students Identified as HHM, *N* = 779. The table reports coefficients, standard errors, and significance from multi-group models performed in MPLUS 7.4 (Muthén & Muthén, 1998-2015). All models control for gender, race and ethnicity, attendance rate, and grade level. Standard errors in parentheses are clustered at the school level. M/E 15 refers to mathematics and ELA scores in year 2015, respectively.