Policy Analysis for California Education

WORKING PAPER

Self-Management Skills and Student Achievement Gains: Evidence from California's CORE Districts

Existing research on self-management skills shows that measures of self-management predict student success. However, these conclusions are based on small samples or narrowly defined self-management measures. Using a rich longitudinal dataset of 221,840 fourth through seventh grade students, this paper describes self-management gaps across student groups, and confirms, at a large scale, the predictive power of self-management for achievement gains, even with unusually rich controls for students' background, previous achievement, and measures of other social-emotional skills. Self-management is a better predictor of student learning than are other measures of socio-emotional skills. Average growth in English language arts due to changing from a low to a high level of self-management is between 0.091 and 0.112 standard deviations, equivalent to almost 80 days of learning.

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Introduction

Increasing evidence shows the importance of non-academic skills for students' academic and long-term success (Heckman, Stixrud, & Urzua 2006; Almlund, Duckworth, Heckman, Kautz, 2011; Heckman & Kautz, 2014; Deming, 2017; Kautz, Heckman, Diris, et al., 2014). While which of these skills – for example, growth mindset, self-efficacy, self-management, or social awareness – to prioritize is not yet clear, researchers have found that self-management, i.e., "the ability to regulate one's emotions, thoughts, and behaviors in different situations" (Transforming Education, 2016; Duckworth & Carlson, 2013), strongly predicts student success (Moffit, Arseneault, Belsky et al., 2011). In a number of small-scale studies, self-management, also known as self-control or self-regulation, has proven to be a better predictor of graduation rates than standardized test scores (Duckworth & Carlson, 2013), and has a larger effect on academic achievement than other personality traits such as agreeableness, extroversion, and openness to experiences (Duckworth & Allred, 2012; Duckworth & Carlson, 2013; Poropat, 2009; Duckworth et al., 2015).

Given the potential importance of self-management for future success, a group of districts in California—the *CORE Districts*—included self-management among its annual student outcome measures to inform decision making. The first six CORE districts, operating under a U.S. Department of Education waiver, began collecting survey-based measures of self-management, among other social-emotional learning (SEL) skills, in 2015 for all students in 3rd through 11th grade (Hough, Kalogrides, & Loeb, 2017).[1] Using these data, we study the distribution of students' self-management across grades and student subgroups and analyze the relation between self-management and gains in student performance on the state's annual standardized tests to assess whether self-management scores predict learning beyond what would be predicted by students' prior performance and background characteristics.

To the best of our knowledge, no studies have described the effects of self-management on standardized tests for a large population of school-aged students. Similarly, no prior study describes self-management gaps between student groups such as those defined by previous achievement, levels of parent education, or English learner (EL) status. The data collected by the CORE school districts offer an opportunity to assess the relation between self-management and educational achievement across a wide range of students and to document the variation among them.

We focus on the following questions: (1) Variation: How do self-management scores vary across grades and student subgroups, both across and within schools? (2) Effects: How

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[1] The districts that initially applied the SEL survey were Los Angeles Unified School District (LAUSD), San Francisco Unified School District (SFUSD), Fresno Unified School District (FUSD), Santa Ana Unified School District (SAUSD), Long Beach Unified School District (LBUSD), and Oakland Unified School District (OUSD). However, OUSD is not included in this study because the survey information cannot be linked to student characteristics and achievement. For more information on the CORE Districts and measures see http://coredistricts.org/why-is-core-needed/core-districts/

does self-management predict academic achievement a year later, controlling for multiple prior achievement scores and demographics? (3) Types: Are the components of self-management—interpersonal and cognitive self-management—equally important for predicting academic achievement? Our primary analyses include the 221,840 students in the CORE districts who were in grades four through seven in 2015 or 2016, who completed the survey in the corresponding year, and whose responses we can link to administrative data on test scores from Spring 2013 to Spring 2017.

In what follows, we review the research literature on self-management to highlight the contribution of this paper, describe the data and methods, report the results, and review the implications.

Self-Management

Researchers have used a range of definitions for self-management, as well as a range of names for a similar set of skills. Self-management is also known as, or at least overlaps with, self-control, self-regulation, self-discipline, willpower, effortful control, ego strength, and inhibitory control, among others (Duckworth & Kern, 2011; CASEL, 2005). All of these terms refer to "controlling, directing, and planning cognitions, emotions, and behavior" (McClelland & Cameron, 2011, p32). Some authors posit that self-management should be considered in relation to a valued goal (Duckworth & Carlson, 2013; Duckworth et al., 2015; Duncan et al., 2007; CASEL, 2005) and to a situation in which there are competing goals. For example, the latest definition proposed by Duckworth and colleagues (2019)[2] defines self-management (or self-control) as "the self-initiated regulation of thoughts, feelings, and actions when enduringly valued goals conflict with momentarily more gratifying goals." The Collaborative for Academic, Social and Emotional Learning (CASEL) proposes a less restrictive definition, stating that self-management is the ability to regulate emotions, thoughts, and behavior in order to delay gratification, motivate oneself, and work toward personal and academic goals (CASEL, 2018). When used in school settings, self-management has been framed within school life. For example, the California Core districts consider self-management as the "ability to regulate one's emotions, thoughts, and behaviors in different [school-related] situations" (Transforming Education, 2016).

Despite differences in names and definitions, researchers generally agree that self-management is a multidimensional construct (McClelland & Cameron, 2011; Duncan et al., 2007; Duckworth & Kern, 2011; Duckworth & Steinberg, 2015; Park et al., 2017). Different disciplines (such as cognitive, developmental, personality, or educational psychology) use different perspectives (McClelland et al., 2011; Duckworth & Kern, 2011). Self-management can involve distinct psychological processes including both cognitive and interpersonal dimensions. For example, cognitive psychologists studying self-management focus on the executive

[2] Duckworth and colleagues used to define self-management as "the voluntary control of attentional, emotional, and behavioral impulses *in the service of personally valued goals and standards* [emphasis added]" (Duckworth and Carlson, 2013; Duckworth et al., 2015).

functions, i.e. processes of attentional flexibility, working memory, and inhibitory control, identified as the cognitive dimension of self-management (McClelland et al., 2010; McClelland, Acock, Piccinin, et al. 2013; McClelland & Cameron, 2012; Duncan et al., 2007). In a classroom setting, these cognitive processes include taking turns, remembering directions for an activity, and persisting on a task (McClelland et al., 2012).[3] Psychologists studying self-management from a personality perspective add an emotional dimension that is responsible for triggering quick responses, such as throwing tantrums, fighting, or interrupting (Duncan & Magnuson, 2011; McClelland, et al., 2012; Park et al., 2017).

Several studies show the importance of self-management for academic achievement (Blair & Raver, 2015; Zhou et al., 2010, Duckworth & Seligman 2005; Hofer et al., 2012; Galla et al., 2018). Field experiments found that programs aimed at developing self-management skills can impact achievement and attainment. These studies mostly focus on early childhood and early elementary school students (see Poropat (2009), Duckworth and Carlson (2013), Duckworth et al. (2019), Pandey et al. (2018), and Durlak et al., (2011) for reviews and metanalysis). The PATHS curriculum (Promoting Alternative Thinking Strategies), for example, develops self-management (or self-regulation) skills in preschoolers and has shown benefits for participants even after entering college (Riggs, et al., 2016; Durlak, et al., 2011).

Much less experimental evidence addresses older students. In fact, to the best of our knowledge, only seven randomized control trials have tested the effects of self-management-related interventions on achievement for students in 5th grade and above (Pandey et al., 2018; Duckworth et al., 2013). These studies present evidence in samples of approximately 100 students (Digiacomo & Chen, 2016; Duckworth, et al., 2011; Duckworth, et al., 2013; Feinberg et al., 2013; Lakes & Hoyt, 2004; Ohrt, Webster & De La Garza, 2014). An exception is the evaluation of the Student Success Skills program, which was evaluated in a sample of 193 predominantly Latinx middle school students. This evaluation showed significant benefits of the program on mathematics and reading achievement (Lemberger, et al., 2015; Bowers et al., 2015). Due to the small sample size, however, researchers are unable to describe heterogeneity in effects across student groups.

Correlational or quasi-experimental studies have estimated the relations between self-management and GPA. These studies have also found consistently positive results. Duckworth et al. (2010), for example, collected data from 182 students annually from 5th to 8th grade and estimated the effect of self-management on GPA growth using a student fixed-effect design exploiting the time variation in self-management skills. Hofer et al. (2012) showed that self-control from 697 8th graders explained substantial variance of GPA growth. Duckworth and Seligman (2005) used self-reported self-discipline among 140 8th graders to predict GPA several years later. All these studies show that self-management benefits GPA growth. However, while GPA is a desirable outcome to improve, studying changes in GPA may not be the best way to

[3] This component is related to grit, but distinct, since self-management entails persevering and aligning actions with any valued goal despite momentarily more-alluring alternatives; while grit refers to doing so on a timescale of years (Duckworth & Gross, 2014).

evaluate whether self-management skills benefit academic learning. Teachers may award grades based not only on student achievement or learning, but also on self-management directly. As a result, these studies may not be identifying the relationship between self-management and learning.

Some research has assessed the relationship between self-management and tests scores—instead of GPA—using correlational methods (Alexander et al., 1993; Blair & Razza, 2007; Duckworth & Seligman, 2005; Galla et al., 2014; Martin, 1989; Valiente et al., 2010). These results have been less consistent. On the one hand, Duckworth et al. (2005) observe that self-management predicts standardized tests scores in two convenient samples of approximately 160 students each, even when controlling by various characteristics and previous achievement. On the other hand, Duckworth et. al. (2012) use administrative data from the 1,364 students in the National Institute of Child Health and Human Development (NICHD) Study of Early Child Care and Youth Development and finds that self-management, as evaluated by children's parents and teachers in 4th grade, does not predict standardized tests scores at 5th and 9th grade after controlling for demographics, IQ measure, and previous achievement.

While not all evidence points to the importance of self-management broadly for academic achievement measured by standardized tests, at least some components of self-management do appear to affect test scores (McClelland et al., 2013; Mischel et al., 1989; Duckworth, Tsukayama, & Kirby, 2013). For example, Duncan et al. (2007), from a meta-analysis of six longitudinal data sets, observe that the attention aspect of self-management (part of the cognitive component of self-management) predicts later achievement, while externalizing behavior (part of the interpersonal or emotional component) does not. Park et al. (2017) similarly find evidence that the cognitive component of self-management predicts report card grades, while the interpersonal or emotional component predicts positive peer relations but not academic achievement. Very little research has compared the predictive power of a comprehensive self-management construct to that of its parts. Our study has the opportunity to contrast the importance of a broad measure of self-management with each of its components.

Few studies analyze the differences in self-management across subgroups. McClelland et al. (2011) focus on self-regulation (self-management) of low-income Latinx students and finds that English Learners (EL) enter school with lower self-regulation than their non-EL peers and that their self-regulation grows at slower rates. Similarly, Duckworth et al. (2015) compare differences by gender to better understand the gender gap in GPA and find that the GPA gap is better explained by self-management than by motivation. They conclude that "will, not want" explains the gap (Duckworth & Seligman, 2006). Our study, together with others such as West et al. (2018) which describes trends in the social-emotional skills using the same data, contributes by describing self-management skills among diverse populations.

Measurement of self-management is not straightforward. Studies have relied on a range of measures including task-based instruments, self-reports, and informant-reports. Duckworth

& Kern (2011), after reviewing 282 studies with multiple methods to evaluate self-management, find that in order to gain a complete vision of self-management, one needs to apply different tasks targeted at different components of self-management. However, applying task-based instruments on a large scale can be time consuming and expensive, particularly for a district or state interested in measuring the self-management of its students. Fortunately, Duckworth & Kern (2011) also find that questionnaires (either informant-reported or self-reported) demonstrate considerably greater convergent validity than task-based instruments. This may be in part because they are able to capture more than one self-management component in less time and with fewer resources. School districts, such as the CORE districts, have opted for this strategy, implementing student surveys to measure students' self-reported self-management.

Nevertheless, limitations of self-reported surveys raise questions on whether their use at scale will be beneficial in informing practitioners and policy makers on students' self-management learning. Among the limitations, Duckworth & Yeager (2016) mention that respondents may not answer honestly or they may not be knowledgeable enough about themselves to rate their self-control levels accurately. In addition, even honest and knowledgeable respondents may have different reference frames depending on their context, inserting biases in their response (Duckworth & Yeager, 2016; West et al., 2016). Our study, together with others such as West et al. (2018), contribute to the understanding of whether self-reported surveys can help guide districts and schools in the development of students' self-management skills.

Our study adds to the knowledge on self-management effects on educational achievement in four ways. First, it assesses the extent to which student self-management in 4th through 7th grades, measured through self-reported surveys, predicts subsequent academic achievement gains in a large, diverse population of students. Second, because of the large and diverse sample, the study describes differences in self-management and the relation between self-management and academic achievement across groups of students, such as EL status, Free or Reduced-Price Lunch (FRPL) eligibility, gender, race, and parent education. Third, the study uses state standardized tests as a measure of academic learning that is comparable across classrooms and schools, instead of a measure such as GPA which could include multiple types of skills, not just academic achievement. Finally, the study distinguishes between two dimensions of self-management – interpersonal and cognitive – to assess whether they are equally predictive of academic achievement gains.

Data

CORE districts started measuring SEL skills through surveys in the spring of 2015 for 3rd to 12th grade. This study relies on survey data from spring 2015 and 2016 between 4th grade and 7th grade because these are the grades for which information is available on academic achievement through state standardized tests a year later and a year or two years earlier to use as controls. Not all the districts applied the survey to 4th grade in the first year (2015). Our analytical sample comprises the 221,840 4th to 7th grade students in the five districts that participated in the CORE survey in Spring 2015 and/or Spring 2016 who answered at least one survey item from each component of the self-management measure and the other three SEL measures and for whom we have information on English language arts (ELA) and math test scores in the year they completed the survey as well as for the following year, and for one (in the case of the 2016 cohort) or two (for the 2015 cohort) years earlier.[4] We use test scores two years earlier for students who responded to the survey in 2015 because California did not apply state tests in the 2014 spring.

The analytical sample represents two-thirds of all students enrolled in a school that participated in the CORE districts survey between 4th and 7th grade in 2015 and 2016.[5] Table 1 presents the characteristics and survey response distributions for the analytical sample compared to the information available for all students in the corresponding districts and grades. The last column in Table 1 displays the difference and the statistical significance between those students included in the analytical sample and those not included. The missing students have lower achievement and self-management scores and are less likely to be eligible for subsidized lunch. The analytical sample also contains slightly fewer African American and White students, and more Latinx and Asian students.

Our analytical sample is predominantly Latinx (66 percent), with a small proportion of students categorized as non-Latinx White, Asian or African American (10, 8, and 7 percent each, respectively). About half the students are categorized as EL and 77 percent are eligible for FRPL. The characteristics of students in the analytical sample who participated in the spring 2015 survey and the spring 2016 survey differ somewhat (see appendix Table A1). When comparing students from the analytical sample by survey year, students participating in the 2015 survey have better test scores and SEL measures within their cohort, and belong to socioeconomically disadvantaged groups in lower proportion than students participating in the 2016 survey. This difference likely results from the 2015 sample including only those students who have been in the sample for four years in a row, while students in the 2016 sample are only required to be in the sample for three years, as highly mobile students tend to be more socioeconomically disadvantaged (see Table A1).

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[4] Forty-four students are missing demographic information we could not infer from the available data and we do not include them in the analytical sample.

[5] According to administrative data from the state of California, there were 328,478 unique students in grades 4th to 7th in the CORE districts during academic years 2014-15 and 2015-16 (who were registered in one school and grade during at least one year). Of those students, 1.61 percent were in schools that did not participate in implementing the SEL surveys while they were enrolled. Of the potential 323,182 unique students from the 880 participating schools in the two years, 84.30 percent completed at least one item of each SEL construct in the CORE survey in at least one year. Of that fraction, 81.42 percent are part of the analytical sample, representing 96.68 percent of schools of the five districts. On average, 64.48 percent of the students enrolled in a school grade in a year are included in the analytical sample.

Table 1. Summary statistics

	All Observations			Analytical Sample			Difference in *vs.* out of Sample
Characteristic	*mean*	*sd*	*N*	*mean*	*sd*	*N*	
Self-Management (std in grade)							
Self-Management full scale	0	1	385423	0.037	0.978	300629	0.168 ***
Cognitive self-management	0	1	385234	0.028	0.984	300629	0.126 ***
Interpersonal self-management	0	1	384627	0.039	0.975	300629	0.181 ***
Test Scores							
ELA 17 (std by grade16)	0.003	1.001	205011	0.058	0.987	161456	0.258 ***
Math 17 (std by grade16)	0.005	1.001	204950	0.054	0.993	161456	0.234 ***
ELA 16 (std by grade15)	0.001	1	423036	0.083	0.974	300629	0.282 ***
Math 16 (std by grade15)	0	1	423448	0.083	0.975	300629	0.288 ***
ELA 15 (std by grade15)	0	1	425443	0.075	0.979	300629	0.255 ***
Math 15 (std by grade15)	-0.002	0.999	426395	0.081	0.974	300629	0.281 ***
ELA 13 (std by grade15)	0.002	0.999	183595	0.034	0.991	139173	0.132 ***
Math 13 (std by grade15)	-0.002	0.997	184599	0.035	0.994	139173	0.154 ***
Student Demographics							
FRPL	0.740	0.439	473621	0.773	0.419	300629	0.089 ***
Parent less than HS	0.238	0.426	474146	0.246	0.431	300629	0.023 ***
Ever ELL based on cat.	0.519	0.500	452223	0.530	0.499	300629	0.035 ***
Female	0.488	0.500	474144	0.500	0.500	300629	0.032 ***
Special Education	0.125	0.330	468422	0.091	0.287	300629	-0.095 ***
White non-Latinx	0.100	0.301	474146	0.095	0.294	300629	-0.014 ***
African American	0.090	0.209	474146	0.071	0.195	300629	-0.050 ***
Latinx	0.633	0.482	474146	0.658	0.474	300629	0.068 ***
Asian	0.073	0.261	474146	0.078	0.268	300629	0.013 ***
American Indian/Alaskan Native	0.063	0.243	474146	0.057	0.232	300629	-0.017 ***
Pacific Islander/Filipino	0.026	0.158	474146	0.027	0.162	300629	0.003 ***
Mixed (non-native)	0.014	0.235	474146	0.013	0.208	300629	-0.002 ***
Other SEL measures							
Growth Mindset	0.000	1.000	375841	0.016	0.992	300629	0.082 ***
Self-Efficacy	0.000	1.000	383914	0.013	0.993	300629	0.062 ***
Social Awareness	0.000	1.000	384194	0.025	0.978	300629	0.115 ***
Grade							
4th grade	0.259	0.438	474150	0.281	0.450	300629	0.062 ***
5th grade	0.271	0.444	474150	0.262	0.440	300629	-0.022 ***
6th grade	0.238	0.426	474150	0.226	0.418	300629	-0.032 ***
7th grade	0.233	0.423	474150	0.230	0.421	300629	-0.008 ***
Non Missing Variables							
Has Self-Management scores	0.811	0.392	474150	1.000	0.000	300629	0.517 ***
Has lag ELA and Math scores	0.898	0.302	474150	1.000	0.000	300629	0.278 ***
Has twice lagged scores	0.846	0.361	474150	1.000	0.000	300629	0.420 ***
Has outcome scores	0.848	0.359	474150	1.000	0.000	300629	0.416 ***
Has other SEL measures	0.790	0.407	474150	1.000	0.000	300629	0.574 ***
Has all demographic variables	0.943	0.231	474150	1.000	0.000	300629	0.155 ***

2013 to 2017 as corresponds), and have scores for the other three SEL measures. For non-continuous variables, columns show the share of students with a particular characteristic. SD shown for continuous variables only. Robust standard errors used. (***p<0.01, ** p<0.05, * p<0.1)

Self-Management Measure*.* The CORE districts administered social-emotional learning (SEL) surveys to students in their classrooms near the end of each academic year. In partnership with TransformEd, the CORE districts defined self-management as the “ability to regulate one’s emotions, thoughts, and behaviors in different situations.” The surveys measured self-management through five statements related to cognitive self-control and four statements related to interpersonal self-control. Items were adapted from Patrick and Duckworth (2013). Students rated how often they behaved as the item described "during the past 30 days," using a 5-category Likert Scale (5=*Almost all the time*, 1= *Never or almost never*). The statements have slight differences in some grades to be age appropriate. Following are the grades three through five items:

- Cognitive items: I came to class prepared. I remembered and followed directions. I got my work done right away, instead of waiting until the last minute. I paid attention and resisted distractions. I worked independently with focus.
- Interpersonal items: I remained calm, even when someone was bothering me. I allowed others to speak without interruption. I was polite to adults and peers. I kept my temper in check.

Using almost identical survey-based questions, Park et al. (2017) find that they are able to measure two distinct components of self-management. We follow their proposed thesis to consider self-management as a composite measure of a cognitive dimension (first five questions) and an interpersonal dimension (last four questions).

To create an overall self-management score, we average the ratings of the nine items, giving them equal weight. For those with missing information, we average any available items. A lower rating corresponds to lower reported self-management. The scale ranges from one to five and has an average of 4.09 with a standard deviation (SD) of 0.68 for all students in grades four through seven, and a scale reliability coefficient of 0.85. We build sub-scales of cognitive and interpersonal self-management using the same approach with the corresponding items. The cognitive and interpersonal components have means of 4.04 (SD: 0.73) and 4.15 (SD: 0.79), respectively; scale reliability coefficients of 0.79 and 0.72, respectively; and a correlation of 0.64. Following West et al. (2018), we standardize each score to have a mean of zero and a standard deviation of one in each grade.

Other SEL measures. The CORE surveys measure three other SEL domains. *Growth mindset*, adapted by Transforming Education from Farrington et al. (2013) and Dweck (1999), measures the extent to which students believe their intelligence is malleable (as opposed to fixed). *Self-efficacy*, adapted from Farrington et al. (2013), measures how students perceive their abilities to perform academic tasks and succeed in classes. *Social-awareness*, adapted by TransformEd from the American Institutes for Research (AIR) and the Collaborative for Academic, Emotional, and Social Learning (CASEL) tool "Student Self-Report of Social and Emotional Competencies" (Transforming Education, 2016), measures perceived interpersonal abilities such as empathizing with others and listening to others' points of view. We create measures for each of these constructs in the same way as for self-management, averaging the corresponding items with equal weights and then standardizing within grades to have a mean of zero and standard deviation of one. Higher scores represent a more empowering level of the corresponding SEL measure. Table 1 provides descriptive statistics.

Student Demographics. Administrative data gathered from each district includes students' gender, race/ethnicity, EL status, parent education (high school graduate or not), and FRPL status. Table 1 provides descriptive statistics.

Test Scores: The administrative data includes standardized test scores in math and ELA from Spring 2013, 2015, 2016 and 2017. Starting in 2015, California students in grades three through eight take the Smarter Balanced (SBAC) assessments in math and ELA. We standardized test scores by grade, year, and subject to have a mean of zero and standard deviation of one. Given that the districts only administer the test in grades three through eight, we can only assess the relationship between students' self-management in one year and their learning between that year and the next—controlling for current and prior performance—by using reports of self-management in grades four through seven.[6] Table 1 shows descriptive statistics of tests scores.

Analytical Strategy

We examine the contribution of each student's reported self-management to his or her achievement using the following regression:

$$Y_{isgt} = \alpha_0 SM_{i(t-1)} + \alpha_1 f\left(Y_{i(t-1)}\right) + \alpha_2 f\left(Y_{i(t-2)}\right) + \alpha_3 X_{i(t-1)} + \alpha_4 SEL_{i(t-1)} + \pi_{s(g-1)(t-1)} + \varepsilon_{isgt}, \quad (1)$$

Where Y_{igst} corresponds to either ELA or math test scores from student *i* in school *s*, standardized within year *t* and grade *g* (*g*= 5,6,7, or 8; *t*=2017 or 2016). We estimate Y_{igst} as a linear or cubic function (depending on the model) of students' available prior achievement, $Y_{i(t-1)}$ and $Y_{i(t-2)}$, in both math and ELA. Because $Y_{i(t-2)}$ is not available in the case of *t*=2016, we use $Y_{i(2013)}$. We include controls for student demographics at time *t-1*, X_{it-1}, if available, or at time *t*, including gender, race/ethnicity, parent education, FRPL eligibility, SPED status, and whether the student has ever been categorized as ELL. We also include school-by-grade-by-year fixed effects, $\pi_{s(g-1)(t-1)}$, that account for the sorting of students into schools and minimize reference bias of self-reported measures (Duckworth & Yeager, 2015; West et al., 2016). Some models also control for the other three SEL measures included in the survey: growth mindset, self-efficacy, and social awareness ($SEL_{i(t-1)}$). $SM_{i(t-1)}$ is our variable of interest, the self-management score of the individual student *i* in year *t-1*, with α_0 providing an estimate of the relationship between self-management in one year and achievement growth over the following year, relying on within-school variation across students. Individual differences are represented by ε_{isgt}, estimated with student-level clustering.

[6] The State of California didn't administer tests during 2014, so there is no information on tests scores the year before Spring 2015. However, test scores administered in 2013 included scores for 2nd grade, which allows us to include in the analysis the same grades from the Spring 2015 CORE survey than the Spring 2016 grades.

The relationship between self-management and achievement gains may not be linear. To address this possibility, we consider a model similar to equation (1) except that instead of a linear control for self-management, it includes a categorical version of the construct, where we tagged students whose self-management score is one standard deviation or more below the cohort mean as “low self-management;” those with one standard deviation or more above the cohort mean as “high self-management,” and the rest as “middle self-management.”

Finally, the two components of self-management may differentially affect achievement. Not only might the cognitive dimension have a different effect than the interpersonal dimension, the dimensions may interact so that the interpersonal dimension is more (or less) important depending on the level of cognitive self-management skills. To address this potential, we run a model similar to equation (1), but using each of the two components of self-management independently (academic self-management and interpersonal self-management), as well as the interaction of the two.

For robustness checks we run the same analyses with different samples. First, we look separately per year, allowing us to observe whether the results are consistent across time. Second, we consider a sample of students who answered all of the self-management items to ensure that each student gets a self-management score based on the same items. As Meyer, Wang, & Rice (2017) show, some items give more information than others and, therefore, SEL scores could be different depending on which item is missed. Finally, we use a less restrictive sample in which students are not required to have prior tests scores other than the one from the same year of the survey. Results across these samples are very similar, with the exception being the estimated effect using students from the 2016 survey only, which is smaller[7] than the other estimates, though still significant and meaningful.

Results

Variation in self-management. Self-management levels vary across subgroups. Some of these differences have been documented by West et al. (2018), though we include additional comparisons by EL status, parent education, and achievement level, as well as within school comparisons for all subgroups. Self-management differences may result from true differences in self-management or from differences in reporting, reference frames, and other issues from self-reported measures.

Figure 1 illustrates the gaps per subgroup, per grade, showing sample-wide gaps on the left and average within-school gaps on the right. Table 2 reports the coefficients and the values for each subgroup as well. Both the illustration and the table consider answers from the Spring 2016 survey only, for simplicity.[8] We report differences of racial/ethnic subgroups compared to

[7] The 2016 cohort has a higher proportion of 4th grade students than the 2015 cohort.
[8] Distributions of self-management are similar or slightly smaller in 2015.

Latinx students because Latinx students represent the majority of the population in the CORE school districts, while non-Latinx Whites represent less than ten percent.

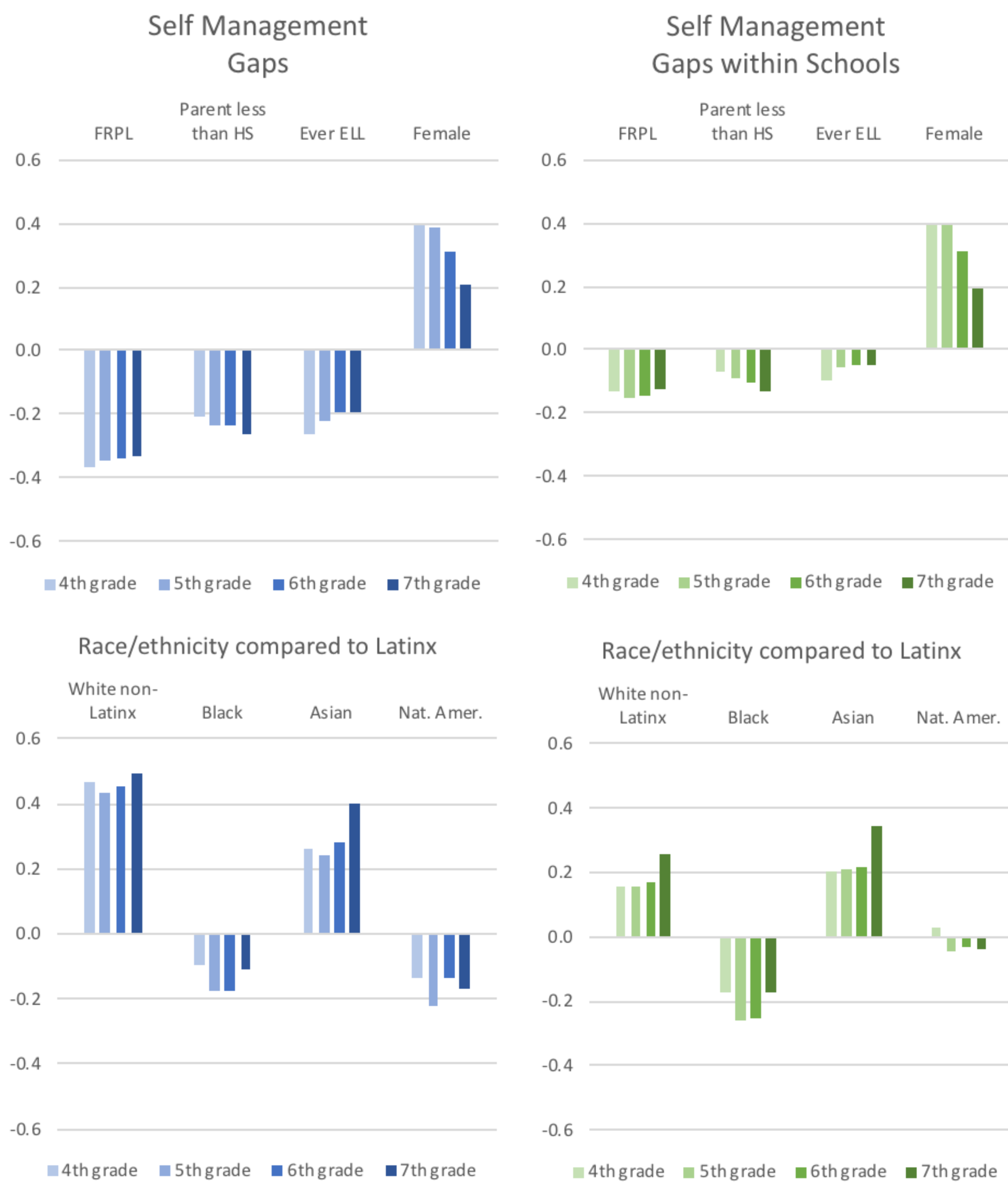
As Figure 1 illustrates, all subgroup differences are significantly different than zero, with the exception of the within-school comparison between Latinx and Native American students. Traditionally lower-performing groups in terms of text performance also tend to groups report lower levels of self-management. The student demographic characteristics that show greater self-management differences are students with special education status (compared to their non-special education peers), followed by non-Latinx White (compared to Latinx students). The White/Latinx gap, though, decreases by half within schools.

Female students report higher levels of self-management than their male counterparts, but the gender gap decreases with age: females show an average of 0.393 SD higher self-management than males in 4^{th} grade, but only 0.205 SD higher in 7^{th} grade. This change is driven primarily by a greater decrease in females' reported self-management than males' decrease. Females' self-management, however, never falls below males, on average, even in high school (see West et al., 2018).

Self-management gaps within schools are generally half the size of sample-wide gaps with four exceptions: the gender gap; the special education gap; and the Asian/Latinx gap, which remain similar in size; and the African American/Latinx gap, which is almost twice as big within schools than sample-wide.

Though self-management gaps are significant across demographic groups, they are largest by achievement levels. Students in the lowest quartile of scores in the districts report between 0.71 and 0.66 SD lower self-management than all other students. Students in the highest quartile report between 0.65 and 0.61 SD higher self-management than the rest of their peers. These gaps are slightly smaller but still very large between students within a school grade. The self-management gaps by achievement remain high at every grade level.

Figure 1. Self-Management Gaps in Spring 2016 By Subgroup and Grade



Note: Race/ethnicity subgroups are compared to Latinx, since more than 70 percent of students are Latinx in sample.

Table 2. Self-Management Gaps per Subgroups (year 2016)

	Panel A: Self-Management Comparison Across Subgroups							
	Students in subgroup			**Comparison group**				
Category	*Self-Manage-ment*	*sd*	*N*	*Self-Manage ment*	*sd*	*N*	Difference between subgroups	Difference b/n groups within schools
FRPL	-0.047	0.997	126038	0.302	0.870	35418	-0.349 ***	-0.139 ***
Parent less than HS	-0.149	1.025	38580	0.086	0.960	122876	-0.235 ***	-0.096 ***
Ever ELL	-0.074	1.001	84868	0.145	0.945	76588	-0.220 ***	-0.063 ***
Female	0.198	0.927	80135	-0.136	1.005	81321	0.333 ***	0.329 ***
Special Education	-0.469	1.081	17737	0.091	0.950	143719	**-0.560** ***	**-0.532** ***
Latinx	-0.028	0.997	103723	.	.	.		
White non-Latinx †	0.434	0.800	15549	-0.028	0.997	103723	0.462 ***	0.185 ***
African American †	-0.166	1.030	11761	-0.028	0.997	103723	-0.138 ***	-0.214 ***
Asian †	0.266	0.847	13325	-0.028	0.997	103723	0.294 ***	0.247 ***
American Indian/Alaskan Native †	-0.199	1.001	10433	-0.028	0.997	103723	-0.170 ***	-0.015
Pacific Islander/Filipino †	0.244	0.845	4240	-0.028	0.997	103723	0.272 ***	0.181 ***
Lowest ELA quartile in school grade	-0.406	1.058	42685	0.186	0.902	118768	**-0.592** ***	**-0.586** ***
Highest ELA quartile in school grade	0.445	0.768	38362	-0.100	1.004	123091	**0.545** ***	**0.542** ***
Lowest Math quartile in school grade	-0.375	1.066	41198	0.168	0.910	120255	**-0.543** ***	**-0.539** ***
Highest Math quartile in school grade	0.413	0.788	37758	-0.087	1.004	123695	**0.500** ***	**0.500** ***
Lowest ELA quartile in whole grade	-0.519	1.068	36701	0.191	0.892	124755	**-0.710** ***	**-0.626** ***
Highest ELA quartile in whole grade	0.505	0.718	42746	-0.141	1.006	118710	**0.646** ***	**0.547** ***
Lowest Math quartile in whole grade	-0.480	1.072	36512	0.179	0.900	124944	**-0.658** ***	**-0.571** ***
Highest Math quartile in whole grade	0.473	0.738	43343	-0.133	1.009	118113	**0.605** ***	**0.510** ***

…. Continued on next page

Table 2 continued. Self-Management Gaps per Subgroups (year 2016)

Panel B: Self-Management Gaps by Grade

	Difference between subgroups†				Difference b/n subgroups within schools†			
Category	4th grade	5th grade	6th grade	7th grade	4th grade	5th grade	6th grade	7th grade
FRPL	-0.367***	-0.349***	-0.341***	-0.334***	-0.134***	-0.150***	-0.146***	-0.126***
Parent less than HS	-0.206***	-0.237***	-0.238***	-0.264***	-0.066***	-0.088***	-0.103***	-0.133***
Ever ELL	-0.260***	-0.219***	-0.193***	-0.194***	-0.098***	-0.055***	-0.048***	-0.047***
Female	**0.393*****	0.391***	0.314***	0.205***	0.392***	0.393***	0.309***	0.193***
Special Education	**-0.538*****	**-0.614*****	**-0.604*****	**-0.473*****	-0.521***	-0.598***	-0.557***	-0.436***
White non-Latinx†	0.469***	0.434***	0.455***	0.493***	0.155***	0.153***	0.168***	0.259***
African American†	-0.098***	-0.178***	-0.177***	-0.109***	-0.172***	-0.261***	-0.254***	-0.176***
Asian†	0.264***	0.239***	0.279***	0.399***	0.205***	0.207***	0.218***	0.345***
American Indian/Alaskan Native†	-0.139***	-0.224***	-0.134***	-0.167***	0.031	-0.043	-0.031	-0.041
Pacific Islander/Filipino†	0.279***	0.244***	0.258***	0.303***	0.160***	0.152***	0.164***	0.234***
Lowest ELA quartile in school grade	-0.583***	-0.620***	-0.604***	-0.557***	-0.576***	-0.620***	-0.597***	-0.549***
Highest ELA quartile in school grade	0.571***	0.573***	0.526***	0.497***	0.570***	0.570***	0.519***	0.495***
Lowest Math quartile in school grade	-0.526***	-0.535***	-0.575***	-0.544***	-0.528***	-0.536***	-0.564***	-0.531***
Highest Math quartile in school grade	0.502***	0.529***	0.493***	0.468***	0.498***	0.526***	0.497***	0.474***
Lowest ELA quartile in whole grade	-0.689***	-0.739***	-0.721***	-0.689***	-0.610***	-0.665***	-0.633***	-0.590***
Highest ELA quartile in whole grade	0.673***	0.661***	0.632***	0.609***	0.582***	0.576***	0.526***	0.491***
Lowest Math quartile in whole grade	-0.641***	-0.649***	-0.696***	-0.656***	-0.559***	-0.574***	-0.603***	-0.551***
Highest Math quartile in whole grade	0.615***	0.605***	0.607***	0.593***	0.521***	0.532***	0.502***	0.479***

Note: Sample described in Table 1 (with no missing demographics). Differences presented correspond to a t-test between both subgroups, with and without school-grade fixed effects. Self-management scores reported have been standardized per grade level. ***p<0.01, ** p<0.05, * p<0.1.
† Comparison group for subgroups by race/ethnicity are Latinx students

Effects of self-management on achievement gains. The primary goal in this paper is to understand whether self-management skills contribute to students' academic achievement. In particular, we ask whether otherwise similar students learn more during the course of a school year if they have greater self-management. Table 3 provides the main estimates. The first column models test scores in ELA (panel A) and Math (panel B) as a function of only self-management measured a year earlier and with grade-school-year fixed effects. The second model adds controls for the prior score in the same subject area. The third model then adds scores in both subjects from two years prior (e.g., tests scores in math and ELA from Spring 2015 and 2016 for students who responded the survey in 2016 and scores from Spring 2015 and 2013 for students who responded the survey in 2015 as California did not administer the test in 2014). Model 4 adds a rich set of student controls; Model 5 adds quadratic and cubic measures of all prior scores; and Model 6 further adds controls for student survey reports of other social emotional measures: growth mindset, self-efficacy, and social awareness. Model 7 reports results allowing self-management to have a non-linear relationship with achievement by separating students into low, middle, and high self-management groups. This model estimates the achievement gap between the low self-management students and each of the other two groups a year later, after controlling for all variables included in model 5.

The coefficient on self-management estimates the average gap in test scores that similar students from the same school and grade have, on average, if their self-management scores differ by one SD. Two students can differ by one SD in self-management if one of them has the average self-management score (approximately 4 in a 1 to 5 scale); that is, if the student reports exercising self-management "frequently" and the other has approximately a score of 4.8 (i.e., the student reports exercising self-management "almost all the time"). Two students can also differ by one SD in self-management if one student has an average self-management score and the other student has a score of 3.4 (i.e., someone who reports exercising self-management "sometimes").

As can be seen in Table 3, Model 1 shows that, on average, students in the same school and grade, but with one SD higher self-management, have 0.316 and 0.290 SD greater ELA and Math scores, respectively, in the following year. Some of that difference is likely due to initially higher achieving students having higher levels of self-management. Once we control for prior scores (Models 2 and 3), we find that a one SD high self-management predicts an approximately 0.052 increase in ELA scores and 0.032 increase in math scores. The estimates are quite robust to the inclusion of student demographics, quadratic and cubic specifications of prior scores and other SEL measures. The estimated increase of having one SD self-management decreases only to 0.042 and 0.033 in ELA and math, respectively, in the model with the lowest estimation, which are all statistically significant. Model 7 in Table 3 reports estimates from a non-linear model of self-management and achievement. The estimated gap in achievement is 0.073 SD between low and mid self-management students and 0.112 between low and high self-management students in ELA. The corresponding numbers are 0.055 and 0.091 in math. These estimates suggest a relatively linear relationship, though with somewhat stronger effects between students with low and medium than with medium and high self-management skills.

Table 3: Effect of Self-Management on Academic Achievement, varying models and samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	School-grade F.E.	Controls by test score on same subject	Adds lag test scores	Adds stud. characteris tics	Adds quadratic and cubic scores	Adds SEL measures	Non-linear SM	2015 only	2016 only	Students with no missing items only	Least restricted sample
VARIABLES					Panel A: ELA (std)						
Self-Management	0.316***	0.071***	0.052***	0.043***	0.042***	0.043***		0.048***	0.036***	0.042***	0.044***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.002)	(0.001)	(0.001)	(0.001)
Middle Self-Management							0.073***				
(ref: Low SM)							(0.003)				
High Self-Management							0.112***				
(ref: Low SM)							(0.003)				
					Panel B: Math (std)						
Self-Management	0.290***	0.056***	0.032***	0.032***	0.033***	0.031***		0.036***	0.029***	0.033***	0.035***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Middle Self-Management							0.055***				
(ref: Low SM)							(0.003)				
High Self-Management							0.091***				
(ref: Low SM)							(0.003)				
ELA & Math scores		yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
ELA & Math twice lagged			yes	yes	yes	yes	yes	yes	yes	yes	no
Student characteristics				yes	yes	yes	yes	yes	yes	yes	yes
Quadratic and cubic scores					yes	yes	yes	yes	yes	yes	yes
SEL measures						yes					
School-Grade-Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	300,629	300,629	300,629	300,629	300,629	300,629	300,629	139,173	161,456	264,033	335,796

Note: Sample in models (1)-(6) corresponds to analitycal sample described in Table 1. No students have missing information in this sample. Self-management score is standardized with mean zero and standard deviation of 1 within each grade. Other SEL measures included in model 6 are social awareness, growth mindset, and self efficacy. Models 8 to 11 use different samples as robustness check: students with SEL information from spring 2015 or 2016 only (Models (8) and (9); students from both years who answered each of the nine self-management items (Model (10)), and the least restricted sample relaxes the restriction of having twice lagged scores (last model). Standard errors in parentheses, clustered by student. *** p<0.01, ** p<0.05, * p<0.1

We run a series of specification checks to the basic models reported in the last four columns of Table 3. The estimates are robust to using different samples and specifications. Checks included separate analyses by year (Models 8 and 9), a sample with only students who answered all nine self-management items (Model 10), and a sample that does not restrict subjects to have information on their twice-lagged performance (Model 11). Relaxing this last restriction allows us to increase the sample, but we cannot control for twice- lagged scores. The analysis shows that the results are robust to different samples and specifications.

Table 4: Effect of Self-Management components on Academic Achievement

	(1)	(2)	(3)	(4)
	Full model	Cognitive S.M.	Interpersonal S.M.	Cognitive and Interp. SM interacted
VARIABLES		ELA		
Self-Management (std within grade)	0.042***			
	(0.002)			
Cognitive Component of SM		0.037***		0.025***
		(0.001)		(0.001)
Interpersonal Component of SM			0.035***	0.022***
			(0.001)	(0.001)
Interpersonal SM * Cognitive SM				0.002*
				(0.001)
		Math		
Self -Management (std within grade)	0.033***			
	(0.002)			
Cognitive Component of SM		0.033***		0.030***
		(0.001)		(0.001)
Interpersonal Component of SM			0.023***	0.007***
			(0.001)	(0.001)
Interpersonal SM * Cognitive SM				0.003***
				(0.001)
ELA & Math scores	yes	yes	yes	yes
ELA & Math twice lagged scores	yes	yes	yes	yes
Student characteristics	yes	yes	yes	yes
Quadratic and cubic scores	yes	yes	yes	yes
School-grade-year FE	yes	yes	yes	yes
Observations	300,629	300,629	300,629	300,629

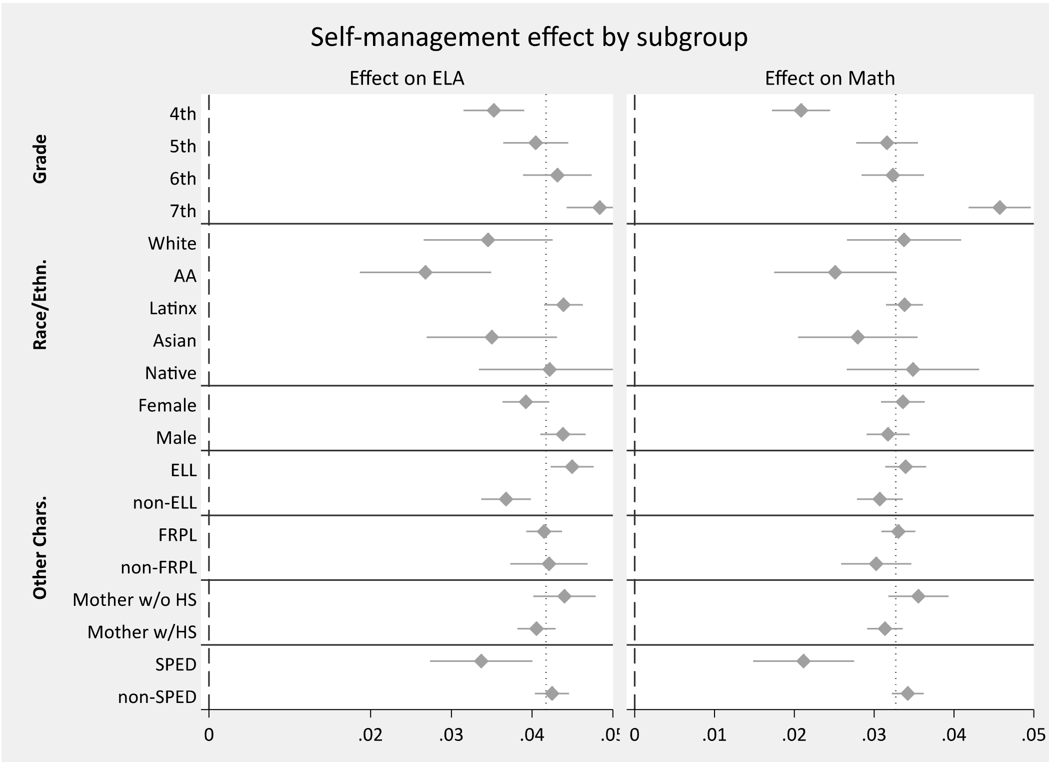
Note: *** p<0.01, ** p<0.05, * p<0.1

Effects of self-management components on achievement gains. Self-management effects may differ depending on which of its components is stronger. Given the evolving nature of these concepts, we assess the extent to which each component varies in predictive power. Models 2 to 4 in Table 4 provide the results. The estimated effects are positive and significant across both components for both ELA and math. The point estimates are approximately the same magnitude for ELA, but the interpersonal component is weaker for math. Model 4 includes both measures and their interaction in the same model. For ELA, again, both components are approximately equally predictive of achievement gains and the interaction term indicates complementarity with each component being more important when the other component is greater. For math, the coefficient on the cognitive component is substantially larger than for the interpersonal component, but both are significant and the complementarity of the two dimensions is, again, evident.

Heterogeneity of self-management effect estimates. The relationship between self-management and achievement may differ systematically across groups. Figure 2a (and Table A2 in the appendix) shows the estimated effects of self-management by grade based on the full model (Model 5 in Table 3). In all available grades the results show a positive relationship between self-management and achievement gains. The point estimates are larger in higher grades (7^{th}) than in lower grades (4^{th}), especially in math. The higher estimates could be due to greater benefits of self-management in higher grades, to more accurate measurement of self-management for older students, or to differences in the population across cohorts.

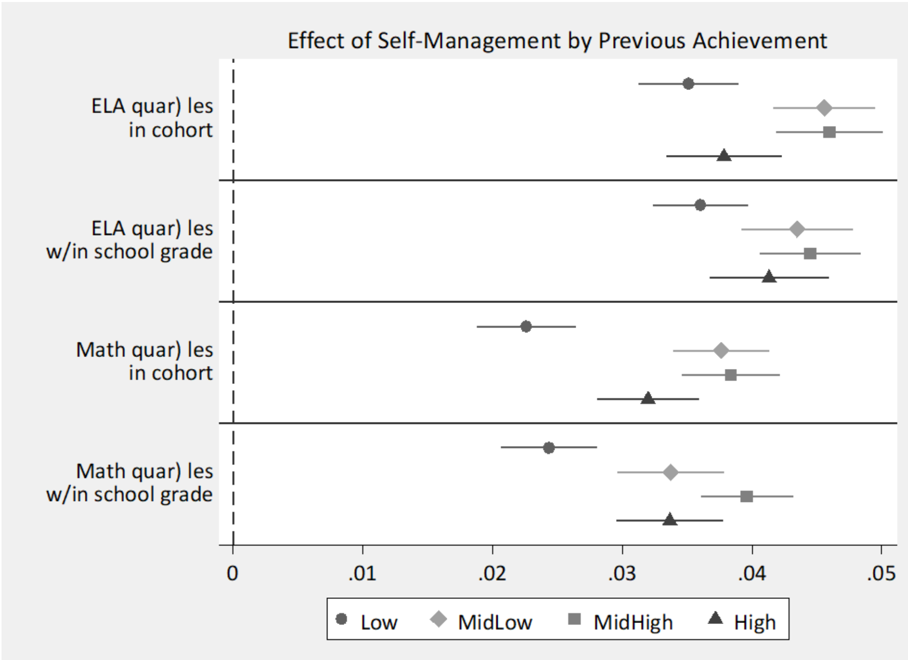
Overall, differences across groups, other than race/ethnicity and special education, are relatively small but significant. Special education students, as well as African American students, show lower increases in achievement from the same reported self-management than the average peer. The opposite is true for EL students, who experience greater ELA growth from the same self-management levels than their non-EL peers. When observing subgroups across the full sample by previous achievement, as illustrated in Figure 2b, students in the middle of the achievement distribution appear to benefit more from self-management skills, though the results are not as evident when we observe quartiles within schools. In math, lower achievers show a weaker relationship between self-management and learning than do middle or high achievers and this difference holds both within schools and across the full sample. Despite these differences, the estimated self-management effects are consistently positive across subgroups. (See Table A2 in the appendix)

Figure 2a. Heterogeneity of self-management effects



Note: Each dot represents the estimated effect of SM on each test (ELA or math) for the corresponding subgroup, as independent regressions, in SD. Lines mark five percent confidence interval of each estimate. Pointed light gray lines show the average effect size using complete sample.

Figure 2b. Heterogeneity of self-management effects by previous achievement

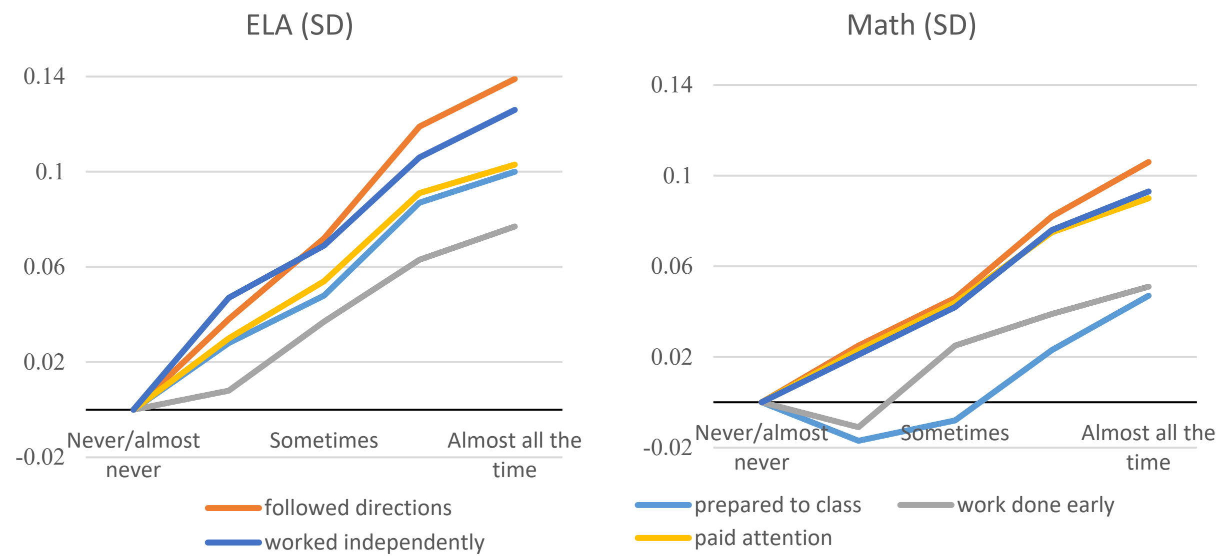


Note: Achievement quarters in cohort and within school grade level. Each dot represents the estimated effect of SM for the corresponding subgroup, as independent regressions, in SD of the corresponding outcome (ELA scores or math scores). Lines mark 5 percent confidence interval.

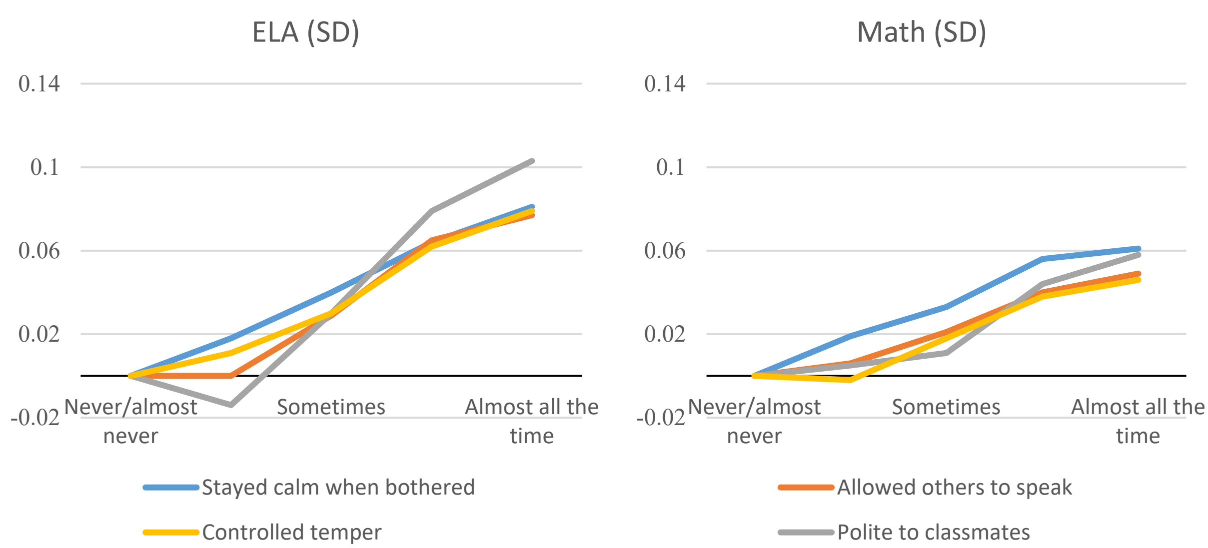
Predictive power of each self-management item*.* School districts and states struggle to find the best ways to measure social-emotional skills. Currently, the most prominent strategy to raise evidence on their students' SEL skills is through self-reported measures in surveys, yet these surveys keep evolving. The self-management instrument included in the CORE district surveys at the time of the study is composed of nine items, of which five correspond to the cognitive component and the other four to the interpersonal component. Given the evolving nature of these instruments, it is worth assessing the extent to which each item varies in predictive power. We run the saturated model (Model 5 from Table 3) replacing the self-management score with each of the self-management items in independent regressions. Students answer each item using a 5-point Likert scale, so we treat the items as categorical. Figure 3 provides the results (also given in appendix Table A3). The lowest score of each item serves as the reference for the other levels. The points in the graph show the difference in the effect size between the corresponding level and the lowest level. The most predictive items in the cognitive component are those asking about following directions, paying attention, and staying focused when working independently. For the interpersonal component, the differences among items are relatively small.

Figure 3. Relationship between achievement and the nine items of the self-management survey instrument

Panel A: Items from the cognitive component of self-management



Panel B: Items from the interpersonal component of self-management



Note: Top panel shows the increase in ELA and math scores gained by each increase in cognitive component items. Lower panel shows results for the interpersonal component items. The Likert scale of items correspond to "Almost Never," "Once in a While," "Sometimes," "Often," and "Almost all the Time."

Discussion

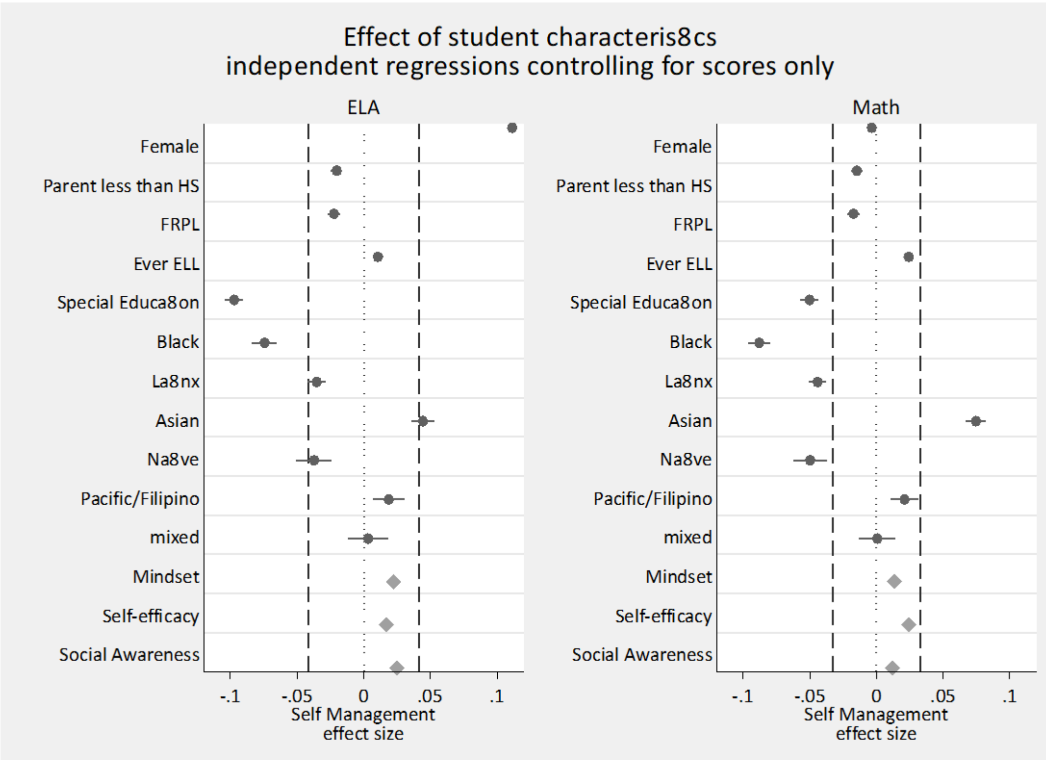
School systems are under increasing pressure to focus on the development of social-emotional skills, in addition to academic skills. Yet, existing research has provided little information about the benefits of these skills at scale. Few studies have addressed potential heterogeneity, or even average effects, for large samples of school-age students. If school systems aim to measure and focus on their students' social-emotional skills, they will need to identify which social-emotional skill to prioritize. Using data collected by five California school districts, this study offers the first evidence we know of that compares the relationship between measures of self-management skills (also identified as self-control) and achievement across a large population of students by subgroups including FRPL status, EL status, and parent education.

We first estimate the levels of self-management for each subgroup. We observe, in keeping with West et. al. (2018), that socioeconomic disadvantage is associated with lower self-management skills. African American, Latinx, and EL students, as well as students eligible for FRPL and those whose parents did not complete high school report lower self-management than their corresponding counterparts. Female students, on average, report higher scores than their male peers, though this advantage decreases as grade-levels increase. These patterns appear within schools as well as across the population, though gaps are generally smaller inside schools, with the exception of the self-management gap between African American students and their non-African American classmates. We find the biggest reported self-management gaps between students with low academic achievement and those with high academic achievement, independent of the subject and independent of whether we compare low and high achievers across districts or within schools.

To study the relationship between self-management and achievement gains, we run a series of regression models controlling for an array of student characteristics, two years of previous achievement scores, and indicators for each school, grade level and year. The school-by-grade-by-year fixed-effects allow us to account for unobserved characteristics of schools that could affect both self-management skills and achievement gains and mask the relationship between them. Moreover, these controls address, in part, the reference bias (Duckworth & Yeager, 2015), the concern that students may report their self-management skills relative to other students in their schools.

The analyses confirm that self-management predicts achievement gains for students when compared within a school and grade, even with unusually rich controls for students' background and prior achievement. The relationship is stronger for self-management than for any of the other SEL skills measured in the CORE surveys (growth mindset, self-efficacy, and social awareness), and is meaningful in size. We estimate that the average growth in ELA scores due to moving from a low level of self-management (i.e., a student who reports exercising self-management "sometimes" or less) to a high level of self-management (i.e., a student who reports exercising self-management "almost all the time") is 0.091 and 0.112 standard deviations in math and ELA test performance, respectively. Based on a rough calculation developed by Hanushek, Peterson & Woessmann (2012), this change is equivalent to almost 80 days of learning, i.e., about four calendar months of school. The difference is especially meaningful considering that the effect of other SEL skills targeted in the CORE survey is less than half the size of the self-management effect size (see Figure 4).

Figure 4. Comparison of effects of different demographic characteristics and self-management effects



Note: Each point is an independent regression controlling by quadratic and cubic lag scores and twice lagged, and no other controls. School grade year fixed effects. The dashed lines represent the effect size of self-management in the most conservative model. See Table A4 in the appendix.

As a second comparison approach, we calculate the effects of several student demographics on achievement, controlling for cubic functions of past achievement in math and ELA. The effect of self-management is greater than, or a considerable proportion of, the effects of each measured demographic as shown in Figure 4 and Tables A4 and A5 in the appendix. For example, the ELA growth gap between FRPL students and non-FRPL students in the same school and grade with similar previous achievement is only 0.022 SD. On the other end, the greatest observed ELA growth gap is the gender gap, estimated as 0.111 SD. The estimated self-management effect is more than a third of the gender gap, even after controlling for gender and all available demographics.

The estimated effects of student-reported self-management skills provide evidence that building self-control may be a useful tool for supporting students' academic learning. This study shows that the positive relationship between self-management and achievement gains may be quite widespread across a variety of schools and student groups. The study also demonstrates substantial variation in reported self-management across student groups, indicating room for improvement. The significant benefits suggested by this study, together with the large proportion of students reporting low self-management skills, (particularly among traditionally under-served student groups), suggest that finding strategies to ensure the development of self-management could help to increase educational equity. However, the research literature has not largely explored how to develop self-management skills, especially at the middle and high school levels (see Duckworth, Gendler & Gross (2014) and Duckworth et al. (2019) for a discussion and up to date review of strategies).

This study also provides some evidence that both components of self-management—cognitive and interpersonal—predict achievement gains and could provide useful information to school systems. The analyses suggest that the two components benefit student achievement independently and interact as complements. Students may benefit from different educational strategies depending on their levels of each component and, therefore, teachers and school leaders may benefit from having information of students' strengths in each separate component.

A consideration to keep in mind is that this study focuses on whether a student with higher self-management than a similar peer *in the same school and grade* will have higher achievement growth. The study does not compare self-management between students from different schools and/or grades because reference-frame bias and self-selection into schools make it difficult to convincingly estimate these differences. Thus, we do not know yet if it would be sensible to compare self-management levels across grades and schools.

While this study is just a first step in assessing the effects of self-management on a large and diverse population of middle school students, it joins a vast amount of evidence on the importance of this skill. Taken together, these findings provide initial evidence of potential benefits of monitoring self-management skills in the population of students even through self-reported surveys. Disaggregating by each component could provide additional information. Yet, not surprisingly, more work is needed not only to understand the beneficial use of these metrics, but also to identify productive approaches to developing students' cognitive and interpersonal self-management skills.

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Appendix Tables

Table A1. Summary statistics for analytical sample per survey year

	Analytical Sample Year 2015			Analytical Sample Year 2016			Difference between 2016 - 2015 Samples	
Characteristic	*mean*	*sd*	*N*	*mean*	*sd*	*N*		
Self-Management								
Self-management scale	0.045	0.975	139173	0.030	0.981	161456	-0.016	***
Cognitive self-management	0.032	0.983	139173	0.024	0.985	161456	-0.007	**
Interpersonal self-management	0.052	0.970	139173	0.029	0.980	161456	-0.023	***
Test scores								
ELA 17 (std by grade year)	0.088	0.967	96189	0.058	0.987	161456	-0.030	***
Math 17 (std by grade year)	0.081	0.975	96244	0.054	0.993	161456	-0.027	***
ELA 16 (std by grade year)	0.105	0.959	139173	0.063	0.987	161456	-0.042	***
Math 16 (std by grade year)	0.099	0.963	139173	0.070	0.986	161456	-0.029	***
ELA 15 (std by grade year)	0.102	0.961	139173	0.052	0.993	161456	-0.050	***
Math 15 (std by grade year)	0.105	0.956	139173	0.061	0.988	161456	-0.045	***
ELA 13 (std by grade year)	0.034	0.991	139173	.	.	.	.	
Math 13 (std by grade year)	0.035	0.994	139173	.	.	.	.	
Student Demograpghics								
FRPL	0.763	0.425	139173	0.781	0.414	161456	0.017	***
Parent less than HS	0.255	0.436	139173	0.239	0.426	161456	-0.016	***
Ever ELL	0.536	0.499	139173	0.526	0.499	161456	-0.010	***
Female	0.504	0.500	139173	0.496	0.500	161456	-0.007	***
Special Education	0.069	0.253	139173	0.110	0.313	161456	0.041	***
White non-Latinx	0.094	0.292	139173	0.096	0.295	161456	0.002	*
African American	0.069	0.032	139173	0.073	0.26	161456	0.004	***
Latinx	0.675	0.468	139173	0.642	0.479	161456	-0.033	***
Asian	0.073	0.26	139173	0.083	0.275	161456	0.009	***
American Indian/Alaskan	0.048	0.215	139173	0.065	0.246	161456	0.016	***
Pacific Islander/Filipino	0.028	0.164	139173	0.026	0.16	161456	-0.001	**
Mixed	0.012	0.271	139173	0.015	0.122	161456	-0.003	***
Other SEL measures								
Growth Mindset	0.022	0.989	139173	0.012	0.994	161456	-0.009	***
Self-Efficacy	0.016	0.992	139173	0.011	0.993	161456	-0.006	
Social Awareness	0.031	0.972	139173	0.020	0.983	161456	-0.011	***
Grade								
4th grade	0.271	0.444	139173	0.290	0.454	161456	0.019	***
5th grade	0.257	0.437	139173	0.267	0.443	161456	0.011	***
6th grade	0.234	0.423	139173	0.219	0.414	161456	-0.015	***
7th grade	0.238	0.426	139173	0.223	0.416	161456	-0.015	***

Note: Each year's analytical sample corresponds to students from the analytical sample described in Table 1 who responded the SEL survey in the corresponding year. There are 78,789 students who answered the survey in both years. In 2015, 4th grade students from two of the districts did not participate. Robust standard errors shown. (***p<0.01, ** p<0.05, * p<0.1)

Table A2: Heterogeneity of the Self-Management effect. Estimation per subgroup

		Effect of Self-Management on Achievement				
		ELA (std)		Math (std)		
Subgroup type	Subgroup	Coeff.	(s.e)	Coeff.	(s.e.)	N†
Grade	4th	0.035***	(0.002)	0.021***	(0.002)	84,604
	5th	0.040***	(0.002)	0.032***	(0.002)	78,909
	6th	0.043***	(0.002)	0.032***	(0.002)	67,934
	7th	0.048***	(0.002)	0.046***	(0.002)	69,182
Characteristics	Non-ELL	0.037***	(0.002)	0.031***	(0.001)	141,205
	ELL ever	0.045***	(0.001)	0.034***	(0.001)	159,424
	Male	0.044***	(0.001)	0.032***	(0.001)	150,407
	Female	0.039***	(0.001)	0.034***	(0.001)	150,222
	Non-SPED	0.042***	(0.001)	0.034***	(0.001)	273,338
	SPED	0.034***	(0.003)	0.021***	(0.003)	27,291
	Non-FRPL	0.042***	(0.002)	0.030***	(0.002)	68,378
	FRPL	0.041***	(0.001)	0.033***	(0.001)	232,251
	Mother w/HS	0.041***	(0.001)	0.031***	(0.001)	226,554
	Mother w/o HS	0.044***	(0.002)	0.036***	(0.002)	74,075
Race/ethnicity	Whites	0.035***	(0.004)	0.034***	(0.004)	28,664
	African American	0.027***	(0.006)	0.025***	(0.005)	11,907
	Latinx	0.044***	(0.001)	0.034***	(0.001)	197,722
	Asian	0.035***	(0.004)	0.028***	(0.004)	23,503
	Native Origin	0.042***	(0.004)	0.035***	(0.004)	17,170
Achievement quartiles w/in state cohort	Lowest	0.035***	(0.002)	0.023***	(0.002)	65,513
	Mid low	0.046***	(0.002)	0.038***	(0.002)	75,611
	Mid High	0.046***	(0.002)	0.038***	(0.002)	79,010
	Highest	0.038***	(0.002)	0.032***	(0.002)	80,495
Achievement quartiles w/in school grade	Lowest	0.036***	(0.002)	0.024***	(0.002)	76,153
	Mid low	0.043***	(0.002)	0.034***	(0.002)	65,156
	Mid High	0.044***	(0.002)	0.040***	(0.002)	86,860
	Highest	0.041***	(0.002)	0.034***	(0.002)	72,457

Note: Each coefficient is estimated using an independent regression that corresponds to the subgroup listed in the second column and the outcome of the corresponding column, based on the full model. This is, controlling by quadratic functions of math and ELA tests scores from two previous years, demographics and school-grade-year fixed effects.

† Observations listed for the subgroups related to the achievement quartiles correspond to the observations counted on the ELA groups. Math groups are similar.

Standard errors in parenthesis, clustered by student. *** p<0.01, ** p<0.05, * p<0.1

Table A3. Effect of self-management on achievement, calculated independently for each item

VARIABLES	(1) I came to class prepared	(2) I remembered and followed directions	(3) I got my work done right away instead of waiting until de last minute	(4) I paid attention and resisted distractions	(5) I worked independently with focus	(6) I remained calm even when criticized	(7) I allowed others to speak without interruptions	(8) I was polite to adults and peers	(9) I kept my temper in check
	Panel A: ELA (std)								
level 2 (ref: level 1)	0.028***	0.038***	0.008	0.031***	0.046***	0.018***	0.009	-0.014	0.011
	(0.011)	(0.011)	(0.007)	(0.007)	(0.008)	(0.005)	(0.006)	(0.010)	(0.006)
level 3 (ref: level 1)	0.048***	0.072***	0.037***	0.059***	0.068***	0.039***	0.029***	0.030***	0.029***
	(0.010)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.006)	(0.009)	(0.006)
level 4 (ref: level 1)	0.086***	0.119***	0.063***	0.091***	0.106***	0.064***	0.065***	0.079***	0.061***
	(0.010)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.005)
level 5 (ref: level 1)	0.100***	0.138***	0.078***	0.103***	0.125***	0.080***	0.077***	0.102***	0.079***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.005)
	Panel B: Math (std)								
level 2 (ref: level 1)	-0.017*	0.025**	-0.011*	0.023***	0.021***	0.018***	0.006	0.005	-0.002
	(0.010)	(0.010)	(0.007)	(0.006)	(0.008)	(0.005)	(0.006)	(0.010)	(0.006)
level 3 (ref: level 1)	-0.008	0.046***	0.015**	0.044***	0.044***	0.033***	0.021***	0.011	0.018***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.005)
level 4 (ref: level 1)	0.023**	0.082***	0.039***	0.074***	0.076***	0.056***	0.040***	0.044***	0.037***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.005)
level 5 (ref: level 1)	0.047***	0.106***	0.051***	0.090***	0.093***	0.060***	0.049***	0.058***	0.046***
	(0.009)	(0.010)	(0.006)	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)	(0.005)
Observations	260,168	260,168	260,168	260,168	260,168	260,168	260,168	260,168	260,168

Note: Coefficients presented in each column in each panel were estimated using the full model presented in Table 3, replacing self-management scale for the discrete version of the item described the corresponding model. The full model controls by quadratic functions of math and ELA tests scores from two previous years, demographics and school-grade-year fixed effects. Standard errors in parenthesis, clustered by student. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Comparing self-management effect with demographics effects

	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	full model	Individual controls						
VARIABLES		Panel A: Effect on ELA						
SM (std by grade)	0.042***	0.051***						
	(0.001)	(0.001)						
Female	0.098***		0.111***					
	(0.002)		(0.002)					
Parent with no high-school	-0.020***			-0.020***				
	(0.002)			(0.002)				
FRPL	-0.020***				-0.022***			
	(0.003)				(0.003)			
ELL this year	0.007***					0.011***		
	(0.002)					(0.002)		
SPED	-0.079***						-0.097***	
	(0.003)						(0.003)	
African American	-0.058***							-0.074***
	(0.007)							(0.006)
Latinx	-0.017**							-0.035***
	(0.007)							(0.004)
Asian	0.049***							0.044***
	(0.007)							(0.005)
	Panel B: Effect on Math							
SM (std by grade)	0.033***	0.033***						
	(0.001)	(0.001)						
Female	-0.014***		-0.004**					
	(0.002)		(0.002)					
Parent with no high-school	-0.014***			-0.015***				
	(0.002)			(0.002)				
FRPL	-0.012***				-0.017***			
	(0.002)				(0.002)			
ELL this year	0.021***					0.024***		
	(0.002)					(0.002)		
SPED	-0.047***						-0.050***	
	(0.003)						(0.003)	
African American	-0.078***							-0.088***
	(0.007)							(0.004)
Latinx	-0.043***							-0.044***
	(0.007)							(0.003)
Asian	0.058***							0.074***
	(0.007)							(0.004)
other race/ethn. controlled	yes							yes
Test scores twice lagged	yes	yes	yes	yes	yes	yes	yes	yes
Quadratic and cubic scores	yes	yes	yes	yes	yes	yes	yes	yes
School-Grade-Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Constant	yes	yes	yes	yes	yes	yes	yes	yes
Observations	300,629	300,629	300,629	300,629	300,629	300,629	300,629	300,629

Note: Standard errors in parentheses. No imputations used (sample restricted to students with all demographic information).

Table A5. Self-management compared with other SEL

	(1)	(2)
	ELA	Math
Self-Management	0.043***	0.031***
	(0.001)	(0.001)
Growth Mindset	0.022***	0.011***
	(0.001)	(0.001)
Self-Efficacy	-0.001	0.016***
	(0.001)	(0.001)
Social Awareness	-0.004***	-0.011***
	(0.001)	(0.001)
Demographics	yes	yes
Test scores twice lagged	yes	yes
Quadratic and cubic scores	yes	yes
School-Grade-Year FE	yes	yes
Constant	yes	yes
Observations	300,629	300,629

Note: All SEL measures are standardized within grade. Standard errors in parenthesis. Sample corresponds to Analytical Sample described in Table 1. *** p<0.01, ** p<0.05, * p<0.1