Article

Educational Policy
1–39

DOI: 10.1177/08959048231209262
journals.sagepub.com/home/epx
Sage

Noncognitive Factors and Student Long-Run Success: Comparing the Predictive Validity of Observable Academic Behaviors and Social-Emotional Skills

Jing Liu[1], Megan Kuhfeld[2] and Monica Lee[3]

Abstract

Noncognitive constructs such as self-efficacy, social awareness, and academic engagement are widely acknowledged as critical components of human capital, but systematic data collection on such skills in school systems is complicated by conceptual ambiguities, measurement challenges and resource constraints. This study addresses this issue by comparing the predictive validity of two most widely used metrics on noncogntive outcomes—observable academic behaviors (e.g., absenteeism, suspensions) and student self-reported social and emotional learning (SEL) skills—for the likelihood of high school graduation and postsecondary attainment. Our findings suggest that conditional on student demographics and achievement, academic behaviors are several-fold more predictive than SEL skills for all long-run outcomes, and adding SEL skills to a model with academic behaviors improves the model's predictive power minimally. In addition, academic behaviors are particularly strong predictors for low-achieving students' long-run

[1]University of Maryland College Park, College Park, MD, USA; IZA Institute of Labor Economics, Bonn, Germany
[2]NWEA, Portland, OR, USA
[3]Stanford University, Palo Alto, CA, USA

Corresponding Author:
Jing Liu, College of Education, University of Maryland College Park, 2203 Benjamin Building, College Park, MD 20742-5031, USA.
Email: jliu28@umd.edu

outcomes. Part-day absenteeism (as a result of class skipping) is the largest driver behind the strong predictive power of academic behaviors. Developing more nuanced behavioral measures in existing administrative data systems might be a fruitful strategy for schools whose intended goal centers on predicting students' educational attainment.

Keywords

student absenteeism, social-emotional learning, educational attainment

Introduction

Expanding the definition of student success beyond academic achievement is a growing focus in U.S. education policy-making. The passage of the Every Student Succeeds Act (ESSA) in 2015, requiring states to adopt a fifth indicator for their accountability systems to evaluate school performance beyond academic achievement, further promoted the use of non-academic outcomes in facilitating education policy-making (West et al., 2016). While there is an ongoing debate around how to label, organize, and interpret the set of skills that fall outside of traditional academic achievement (Duckworth & Yeager, 2015; Humphries & Kosse, 2017), the term "noncognitive" is commonly used to refer to this broad set of abilities (Jones, 2021). As Messick (1979) states, this term is primarily defined by what it is not: "Once the term cognitive is appropriated to refer to intellective abilities and subject-matter achievement in conventional school areas…the term noncognitive comes to the fore by default to describe everything else" (p. 282). A wide range of constructs have been grouped into the bucket of noncognitive factors, including skills that are traditionally grouped as being related to social and emotional learning (SEL, such as grit, self-efficacy, and social awareness) and those that fall under an "academic behavior" domain (e.g., school attendance, externalizing behaviors).

In a broad sense, SEL refers to the "process through which individuals learn and apply a set of social, emotional, and related skills, attitudes, behaviors, and values that help direct their thoughts, feelings, and actions in ways that enable them to succeed in school, work, and life." (Jones et al., 2021). Decades of research in education, psychology, economics, and other disciplines suggest SEL skills are comprised of a wide variety of skills that are highly malleable (Durlak et al, 2011; Revelle, 2007), can be purposefully nurtured in schools (Jackson et al., 2020; Loeb et al., 2019), and are highly consequential for student life outcomes (Cunha et al., 2010; Deming, 2017; Heckman et al., 2006). Due to these reasons, there has been a surge of interest in using SEL skills as a measure of student outcomes in education systems.

Academic behaviors are another category of noncognitive factors that are often collected systematically in schools and districts (Farrington et al., 2012). We use the term academic behaviors to describe a set of widely adopted behavioral measures, including attendance/absenteeism and suspensions as well as behaviors like on-time homework completion. The requirement that schools collect and report a non-academic indicator under ESSA made observable academic behaviors an accessible choice for systematic data collection. Indeed, 36 states and the District of Columbia report chronic absenteeism as the fifth indicator of school quality under ESSA (Woods, 2018). Influenced by a variety of personal, school, family, and community factors, academic behaviors also have been proven to be quite consequential for a host of short- and long-run student outcomes (e.g., Bacher-Hicks et al., 2019; Davison et al., 2022; Liu et al., 2021; Sorensen et al., 2022).

SEL skills and academic behaviors are related in multiple ways. For example, self-discipline, a widely used SEL domain that indicates the ability to suppress prepotent responses in the service of a higher goal, is shown to consistently predict school attendance for adolescents (Duckworth & Seligman, 2006). Similarly, schools with exclusionary discipline are linked to a lower sense of belonging for the students (McNeely et al., 2002). Given the sheer number of separate but related competencies, how should schools prioritize and use the various measures of student skills and behaviors beyond academic achievement? Bringing clarity to these related constructs is important as the field further embraces the use of noncognitive outcomes for accountability, school improvement, and many other policy purposes. Schools also have only limited resources, but data collection efforts, such as survey-based measures, can be costly.

One potentially useful way to elucidate the above question is to assess the association between a variety of noncognitive indicators and educational attainment, and the relative predictive power of these different indicators on a student's long-run success. While data collection efforts on both academic behaviors and SEL skills have many different policy and practical applications, we argue that this prediction exercise can serve as a useful first step toward clarifying the relationships between the various noncognitive indicators in a single empirical framework. Notably, this predictive framework is derived from early warning systems (EWS), which are now widely adopted by K-12 schools around the nation to flag students who may be at risk of falling behind. The goal of such predictive frameworks used in EWS is not to compare the *causal impacts* of different student measures on their educational attainment, but identifying variables that contribute the most information to the prediction of these longer-run outcomes. The EWS literature consistently finds that attendance, behavioral infractions, and completion of certain high-stakes academic coursework are the strongest predictors of high school graduation above and beyond standardized test scores (Allensworth, 2013; Balfanz et al., 2007). Measures such as SEL skills are rarely included in EWS, however, presumably due to the cost and measurement issues mentioned above.

To date, most research on the relationship between noncognitive indicators and longer-run outcomes has either focused on a single measure at a time or created some sort of large composite of multiple measures (e.g., Jackson et al., 2020). The strong predictive validity of academic behaviors such as absenteeism in particular is often used to justify the use of these measures in school accountability systems, but systematic data on noncognitive factors can offer many other uses. However, if measures of SEL skills uniquely predict educational attainment, then having measures of SEL skills directly included in an accountability system might help improve a school's ability to identify students who are at risk of dropout or who may be less successful in postsecondary attainment. This could help policymakers decide whether the benefits justify the cost of collecting and assessing data on noncognitive factors beyond those that are currently examined. Thus, we argue that the knowledge about the relative predictive validity of various noncognitive skills to key student life outcomes serves as an essential starting point for educational policy-making in this focal area.

In this study, we simultaneously evaluate the degree to which observable academic behaviors and student self-reported SEL skills measured in ninth grade predict future educational attainment, including on-time high school graduation, postsecondary enrollment, and post-secondary persistence. To do this, we use detailed longitudinal data from a large urban school district in California. Our observable student behaviors include full- and part-day school absenteeism and suspensions in ninth grade. Our SEL constructs include self-management, self-efficacy, growth mindset, and social awareness from a survey administered in each cohort's ninth grade year. We also consider how the relative predictive validity between the two sets of noncogntive factors varies by student racial/ethnicity identity and prior achievement.

Background

In this section, we systematically describe the conceptualization and measurement of two broad categories of noncognitive factors: SEL skills and academic behaviors. Specifically, we discuss the constructs these measures capture, challenges with their measurement, their inter-correlations, their use in education policy, and their association with student long-run outcomes.

In light of such scattered inquires in this field, to date there are multiple conceptual frameworks that have attempted to organize the various components of noncognitive factors. For example, a report from the University of Chicago Consortium on Chicago School Research organizes noncognitive factors into five categories: Academic behaviors, academic perseverance, academic mindsets, learning strategies, and social skills (Farrington et al., 2012). The Chicago model purposefully use the word ‘‘factors’’ instead of ‘‘skills,’’ intending to broaden the concept by including behaviors, skills, attitudes, and strategies. In contrast, other frameworks are more narrowly focused on the ‘‘skill’’ side of noncognitive factors and use slightly different conceptualizations. The Collaborative for Academic Social and Emotional Learning (CASEL) explicitly uses the term ‘‘social and emotional learning’’ skills to cover similar competencies as noncognitive skills and provides another widely adopted model, including self-awareness, self-management, social awareness, relationship skills, and responsible decision-making. Yet another term—‘‘21st-century skills’’—is popularly used to emphasize the value of critical thinking and problem-solving skills as a means for college and career readiness (Council et al., 2012).

Social-Emotional Skills

Most education policymakers would agree that cultivating noncognitive skills are important for student success. Indeed, some practices exist to gage and collect data on noncognitive skills in a systematic manner. For example, the CORE partnership in the state of California[1] administers social-emotional and school climate and culture surveys annually to students across nine large school districts, first as part of a No Child Left Behind waiver received in 2013 and then to build a school performance measurement system that incorporates social and emotional learning (SEL) and school culture and climate (Hough et al., 2017).

Within the context of our study, we focus on four prominently used measures of key SEL constructs that have been collected by the CORE districts: growth mindset, self-efficacy, self-management, and social awareness. While by no means a comprehensive list of SEL skills, these constructs are selected by the CORE districts based on the extent to which they are meaningful, measurable, and malleable (Krachman et al., 2016). The CORE districts also prioritize identifying at least one intrapersonal skill and one interpersonal skill to ensure that there is a broad range of noncognitive skills represented.[2] Each CORE construct is defined and described in more detail below.

Growth Mindset. Growth mindset refers to the belief that one's abilities can grow with effort (Blackwell et al., 2007). Having a growth mindset is often associated with whether students exert effort in school (Dweck & Yeager, 2019). As a result, students randomized to receive growth mindset interventions demonstrated higher grades and higher enrollment in advanced mathematics courses (Yeager et al., 2019), which has been found to predict high school completion (Farrington et al., 2012).

Self-Efficacy. Self-efficacy is the belief in one's ability to succeed in achieving a goal, such as one's ability to attain a certain educational outcome (Bandura, 1993). Self-efficacy is associated with achievement, attendance, and educational attainment (Zimmerman et al., 1992; Dweck et al., 2014).

Self-Management. Self-management (also known as ''self-control'' or ''self-regulation'') is the ability to regulate one's emotions, thoughts, and behaviors effectively in different situations (Core Districts, 2021). Self-management is associated with higher grades and school attendance (Duckworth & Seligman, 2005, 2006), and being financially stable as adults (Moffitt et al., 2011).

Social Awareness. Social awareness is the ability to take the perspective of and empathize with others from diverse backgrounds, as well as to understand social and ethical norms for behavior (Core Districts, 2021). Social awareness has been found to be moderately correlated with GPA and students test scores in middle and high school (West et al., 2018), though the relations between social awareness and achievement are typically indirect (Farrington et al., 2012).

Leveraging SEL skills to gage student noncognitive skills has great value, but concerns still remain. Akin to measuring academic skills, understanding gains in SEL can give schools the ability to adjust their programing, curricula, and interventions to foster more equitable learning environments. While the idea of measuring SEL skills is typically universally supported and considered useful (DePaoli et al., 2017), little to no guidance exists on the actual process of collecting and using these measures. It is challenging to make decisions on the best-fit SEL assessment out of the myriad available, how to analyze the results, and which adjustments to make based on the insights that data provide. Additionally, many experts caution against the use of self-report data for any high-stakes accountability purposes due to issues with reference bias and relative ease of manipulability (Dweck & Yeager, 2019) relative to so-called objective measures like the total number of absences. Lastly, collecting student survey data to gage student noncognitive ability is often costlier than deriving it from previously-existing administrative data, which can be a considerable barrier for less-resourced schools and districts.

Academic Behaviors

Academic behaviors such as absenteeism and disciplinary infractions are considered part of academic engagement, which consists of elements such as student attendance, classroom participation, adherence to instructions, and assignment completion (Rumberger & Larson, 1998). Behaviors that indicate either engagement or disengagement are essential in their own right, as engagement in schools is a first-order condition that must be fulfilled for a student to flourish socially and emotionally in schools. These behaviors are often strongly tied to constructs falling in the category of SEL skills. For example, self-management is a widely used SEL skill that indicates the ability to regulate one's emotions and behaviors. A student with high self-management skills should at least partially manifest such qualities through low levels of absenteeism and behavioral issues in school (Duckworth & Seligman, 2005).

Absenteeism. Attendance is an example of an observable school-based behavior used by researchers to proxy for the ability to engage in schools. At the most fine-grained level, academic engagement can be observed within the context of a given task, like verbally answering a teacher's question or completing one's homework assignment (Woodward & Munns, 2003). Absenteeism is much more easily observable and measurable, making it relatively less challenging than other measures to use as a proxy for disengagement. Attendance is marked daily, if not multiple times a day among secondary school students, and kept as administrative data. Additionally, school staff also tend to mark reasons why a student has missed school, such as for excused and unexcused reasons, which helps provide an understanding of whether the absence occurred due to legitimate reasons.

Suspensions. School discipline is also considered a measure of noncognitive skills used by researchers (e.g., Holt & Gershenson, n.d; Jackson et al., 2020). Disciplinary infractions often occur due to student misbehavior or disruptive behavior, which may stem from a lack of self-regulation skills (Lochman et al., 1993), issues developing prosocial behaviors (Lochman et al., 1993), or similar. Additionally, when students are suspended from school, they miss out on instructional time just as they might be due to any other absence, signaling disengagement from schools as well. This can create a vicious cycle as when students are engaged, they participate and respond thoughtfully to academic tasks, reducing the possibility of behavioral misconduct. Promoting growth in noncognitive skills is considered a preventative measure for disengagement, thereby reducing incidence of disciplinary infractions such as suspensions (Fredricks et al., 2004).

Individual versus Environmental Factors. While the ease of accessing and collecting academic behavioral measures serves as a huge advantage, the use of absenteeism and suspensions as measures of noncognitive skills poses challenges for research and practice because they are particularly susceptible to the influence of environmental factors. For example, family environment risk factors such as low family cohesion are particularly strong predictors for high absenteeism (Fornander & Kearney, 2019). Students who feel connected to their peers and adults at the school are more likely to attend school regularly (Schanfield et al., 2019) and are less likely to be suspended (Brown et al., 2010), which implies that measures like attendance or suspensions can be capturing a student's level of engagement as well as the extent to which they feel connected to those around them.

Additionally, there exists documented disparities in the relationship between academic behaviors and academic outcomes. Research suggests that low-achieving students, low-income students, and students of color have higher absences and are more likely to receive exclusionary discipline due to environmental factors such as a punitive and unwelcoming academic environment (Brown et al., 2010), teacher and administrators' implicit bias (Barrett et al., 2021; Gilliam et al., 2016; Liu et al., In Press), or pre-existing trauma (Gregory & Fergus, 2017). These disparities, which exist often along lines of socioeconomic status, and race/ethnicity background, suggest that the relationship between academic behaviors and academic outcomes may vary by context as well as access to opportunities afforded to students across contexts. Because of this, solely using behavioral measures to gage student noncognitive ability comes with the risk of also measuring environmental factors driving student behavior in such ways.

Relationship Between Academic Behaviors and SEL Skills

According to the framework by Farrington et al. (2012), academic behaviors and SEL skills are closely related to one another, as a student's self-perceptions can manifest through academic behaviors such as attending school regularly and disciplinary infractions, and academic behaviors can also affect student self-beliefs. Academic behaviors are positively correlated with other complementary factors that support a student's ability to incorporate themselves into the schooling culture, such as a sense of belonging (Neel & Fuligni, 2013) and perceived likeability by others (De Laet et al., 205; Ladd et al., 2008). Furthermore, there is evidence that SEL skills are associated with behavioral measures of engagement, such as strong attendance rates (Kanopka et al., 2020; Schanzenbach et al., 2016). Conversely, disengagement is commonly linked to feelings of isolation or lack of support (Osher & Kendziora, 2010), bullying (Juvonen & Graham, 2014), and a lack of sense of safety (Resnick et al., 1997). Suspensions, a measure of disengagement, has been linked to an increased risk for depression (Rushton et al., 2002), and schools with exclusionary discipline policies tend to have students with lower rates of academic connection and sense of belonging in their classrooms (McNeely et al., 2002). Generally, evidence in the field also suggests that school programs focused on SEL development and restorative justice practices can also lead to reductions in absenteeism and/or suspensions (Durlak et al., 2011; Belfield et al., 2015; Jones et al., 2015; Gonz'alez, 2015).

Predictive Validity of Academic Behaviors and SEL Skills

Extensive literature documents the association between each of the noncognitive measures defined above and student outcomes. For academic behaviors, an emerging literature starts to build strong links between absenteeism and exclusionary discipline and an array of student life outcomes, including criminal justice contact, social safety net program participation, education attainment, and performance on the labor market (Bacher-Hicks et al., 2019; Davison et al., 2022; Liu et al., 2021; Sorensen et al., 2022). For example, a recent paper estimates that 10 total absences in ninth grade reduce both the probability of on-time graduation and ever enrolling in college by 2% (Liu et al., 2021). Evidence also exists on the negative impact of school discipline on short- and long-run outcomes. Bacher-Hicks et al. (2019) leverages exogenous variation in school assignment caused by school attendance boundary change and finds that students assigned to a school that has a one standard deviation higher suspension rate are 15% to 20% more likely to be arrested and incarcerated as adults. Davison et al. (2022) attributes at least 30% of the differences between Black and White students on important outcomes in young adulthood such as criminal justice outcomes and college completion to differential exposure to school discipline.

Similarly, a growing body of research provides evidence on the importance of SEL skills (above and beyond the effect of cognitive ability) to long-term educational outcomes like high school graduation and workforce outcomes like earnings (Almlund et al., 2011; Belfield et al., 2015; Dweck et al., 2014; Heckman & Vytlacil, 2001). Research continually demonstrates the value of students' SEL skills, such as growth mindset and self-management, in determining their future success, including academic achievement, workforce performance, and well-being (De Ridder et al., 2012; Moffitt et al., 2011; Jones et al., 2015; Cunningham & Villaseñor, 2016). For example, important SEL factors are shown in meta-analyses to promote success in school and life (Durlak et al., 2011; Taylor et al., 2017; Poropat, 2009). Their predictive power exceeds that of cognitive skills after controlling for educational attainment (Heckman et al., 2014; Segal, 2013). In addition, social and emotional skills in childhood predict higher long-term earnings and better financial situations in adulthood (Chetty et al., 2011). Several longitudinal studies have also found statistically significant associations between measures of SEL skills and key young adult outcomes, across multiple domains in education, criminal activity, substance use, and mental health (Hawkins et al., 2008; Jones et al., 2015).

While the individual association between a particular noncognitive skill to student long-run success is well established, little research approaches this question in a comprehensive manner that integrates all noncognitive skills hand in hand. In particular, research has shown that students who exhibit behaviors associated with dropping out—including course failures, chronic absenteeism, and suspensions—also have lower scores on measures of SEL constructs like self-management (Soland et al., 2018). Humphries & Kosse (2017) is a paper that is most related to the current study in the sense that it compares the relative effectiveness of multiple noncognitive skills in one study. Using a national representative survey dataset from Germany, the authors construct measures of personality traits, risk and time preference, and IQ.

Data

Our paper uses a rich administrative dataset containing student demographic, academic, and SEL information collected from a large, urban school district in California. The sample we examine consists of two cohorts of students, who were enrolled in the district as ninth graders in 2015 and 2016. We link each student and their demographic information to three additional datasets from the same (i.e., ninth grade) school year: (1) detailed, course-level attendance data; (2) discipline data, which include both number of suspensions and total suspended days; and (3) student responses to the annual CORE SEL survey. Additionally, to measure our outcomes, we link each student to their long-run academic outcomes, as proxied by on-time high school graduation status and postsecondary attainment.

Measures of Observable Academic Behavior

The attendance dataset used in this paper, derived from district administrative data, uniquely allows us to examine absences at a granular level beyond the measures traditionally considered in attendance research. Specifically, we observe student absences for each course and day that the student is enrolled. In turn, we are thus able to observe whether a student misses a single class on a given day or all of their assigned classes on a given day. This adds significant nuance to our data, as most typical research studying student absenteeism defines an absence as missing a full day of school. However, recent studies have documented a greater prevalence of partial-day absences among secondary school students compared to full-day absences, and that the traditional definition of full-day absences may leave missed days unaccounted for (Whitney & Liu, 2017). Accordingly, we calculate partial and full-day absences for each student and account for both measures in our analyses. The suspension variables are similar to what is included in most administrative datasets, which provide both the number and duration of suspensions a student has received. The reliability of our attendance and suspension data have been verified in other studies using this same dataset (Liu et al., 2021; Liu et al., In Press; Whitney & Liu, 2017).

Measures of Self-Reported SEL

In this paper, we focus on four SEL constructs in particular: self-efficacy, self-management, growth mindset, and social awareness. Appendix B describes the items used in the survey to measure each construct. Within the context of our paper, self-efficacy is the belief that a student is capable of achieving a given academic outcome; self-management is the student's belief that one can regulate emotions, thoughts, and behaviors, especially in challenging circumstances; growth mindset is belief that academic ability is not fixed, but rather grows with effort; and social awareness is the ability to understand norms, empathize with others, and respect others' perspectives.

In an annual survey administered halfway through each school year (i.e., roughly February), students respond to a range of 4 to 8 questions for each construct using Likert scale-style responses that measures the extent to which they agree with each given statement. In our analyses, we use means of each construct from surveys that each cohort took during their ninth grade school year that are standardized at the cohort level.[3] The survey response rate is approximately 67% over the years we examine.

Although there are numerous ways to measure these SEL constructs, the particular survey from which we derive our SEL measures have been examined extensively in recent analyses. Evidence suggests that the four constructs we consider in our paper have generally high levels of reliability and validity (Meyer et al., 2018). Specifically, Cronbach's alpha for the ninth grade survey forms ranges from .75 to .90 (Meyer et al., 2018), and the four SEL constructs are strongly correlated with concurrent academic and behavioral outcomes (West et al., 2018). Additionally, reports have indicated high fidelity during survey implementation and that student guessing or lack of motivation are not issues that impose serious issues to data quality (Vriesema & Gehlbach, 2021).

Long-Run Outcomes

The dependent variables we use to gage impact of noncognitive skills on long-term success are derived from two sources. First, we derive high school graduation outcomes from district-level administrative data that track the range of graduation criteria that students meet. Most students are categorized as having graduated successfully based on results from the corresponding state's high school exit exam, although a small proportion of students qualify as a high school graduate via other pathways, such as the GED. Second, we observe students' postsecondary enrollment via links to National Student Clearinghouse (NSC) data. Our college-level outcome measures include a dummy variable for whether students enroll in college immediately after graduating high school, and a dummy variable for persistence, defined as whether students enroll in two consecutive years of college immediately after graduating high school.

Descriptive Statistics

Table 1 presents descriptive statistics first for our full analytic sample ($N = 8{,}606$) and then by cohort ($n = 4{,}424$ for Cohort Year 2015, and $n = 4{,}182$ for Cohort Year 2016). We focus on describing the full sample because the two cohorts appear to be largely similar in both their demographic composition and educational attainment, but highlight differences between the two cohorts when they are present. Overall, 47% of the ninth graders in our sample are female. Notably, the district in which this study takes place is socioeconomically and racially diverse. In total, 45% of the students are Asian, 10% are Black, and 31% identify as Hispanic. The rest

Table 1. Descriptive Statistics.

	All Students		Cohort Year 2015		Cohort Year 2016	
	Mean (1)	*SD* (2)	Mean (3)	*SD* (4)	Mean (5)	*SD* (6)
Demographics						
Female	0.47		0.45		0.49	
Asian	0.45		0.45		0.45	
Black	0.10		0.10		0.10	
Hispanic	0.31		0.31		0.30	
Other Race/Missing Race	0.05		0.05		0.05	
White	0.09		0.09		0.10	
Special Education Flag	0.12		0.12		0.11	
Gifted Flag	0.33		0.34		0.33	
Parent with College Education	0.32		0.32		0.15	
English Learner	0.51		0.51		0.52	
Academic Behaviors						
Ninth Grade GPA	2.97	(1.00)	2.85	(1.05)	3.10	(0.92)
Full-day Absences	6.33	(13.08)	6.16	(13.35)	6.51	(12.79)
Part-day Absences	16.66	(21.30)	17.60	(22.23)	15.65	(20.21)
Suspended 1+ times	0.02		0.02		0.02	
Total Number of Days Suspended	0.07	(0.68)	0.08	(0.68)	0.06	(0.69)
SEL Skills						
Self-Management	4.07	(0.61)	4.08	(0.59)	4.06	(0.62)
Growth Mindset	3.72	(0.91)	3.66	(0.88)	3.78	(0.93)
Self-Efficacy	3.40	(0.93)	3.42	(0.93)	3.38	(0.93)
Social Awareness	3.61	(0.62)	3.62	(0.61)	3.60	(0.63)
Educational Attainment						
On-Time Graduation	0.74		0.75		0.74	
Attended College Immediately After HS	0.68		0.65		0.72	
Persistence in second Year of College	0.60		0.60		N/A	N/A
N	8,606		4,424		4,182	

Note. Data come from ninth graders who enrolled in the anonymized district in school years 2015 and 2016. Full-day absence is a count variable of instances when total number of class absences divided by the total number of class meetings equal exactly one, while part-day absence is a count variable of instances when it equals a value between zero and one (indicating partial attendance). Descriptive statistics of SEL measures are means of items within each composite in raw scores. We standardize all the SEL measures at the cohort-grade level in our analysis. Missing values are treated as zeros.

of the cohort (14%) are composed of White students, other racial groups, or students for whom we do not have race/ethnicity information in the administrative data. Fewer than half of the students in the sample (32%) have a parent who has completed a college education, a salient statistic given that we examine the predictive validity of students' various measures on their long-run college attainment outcomes. About 12% of the students are classified as having special needs, and 33% are identified as gifted students. The average cumulative GPA is approximately 2.97 at the end of the ninth grade year.

In terms of observable academic behaviors, the average student in our sample missed about six full school days during ninth grade. In contrast, part-day absenteeism is much more prevalent; the average student accrues about 17 part-day absences, or close to three times as many as full-day absences. This is consistent with prior research that shows part-day absenteeism accounts for more than half of total absenteeism in secondary schools (Whitney & Liu, 2017). Additionally about 2% of all students receive at least one suspension in ninth grade, and the number for average suspended days across all students is 0.07. Lastly, we examine measures of self-reported SEL skills across the sample and by cohort, which are standardized by cohort to have a mean of zero and a standard deviation of one.

Approximately 74% of the ninth graders in our analytic sample graduated high school on time, and 68% of the students went to college immediately after high school. For the 2015 cohort, about 60% persisted and enrolled in two consecutive years of college.[4]

Correlations Between Self-Reported SEL and Academic Behaaviors

Before examining the predictive validity of our chosen noncognitive metrics, we first investigate associations that may exist between said metrics. As described before, we anticipate some correlations between our measures of noncognitive factors based on the prior literature. We use two approaches to do this. First, we use Pearson correlation to evaluate how each of the observable academic behaviors and SEL skills correlate with a different measure. Second, we conduct a factor analysis to examine the common variance from all the variables.

We present pairwise correlations in Table 2. First, unsurprisingly, we observe meaningfully large correlations between measures *within* each set of noncognitive metrics. For example, the strongest correlation is between self-management and growth mindset (p = .53), followed by that between part-day and full-day absenteeism (p = .45). The negative correlation between absenteeism and suspension is statistically significant, but very small in magnitude (p = −.10). Additionally, we observe statistically significant correlations between measures *across* the two sets of noncognitive metrics of interest. As expected, there is a negative correlation between the academic behavioral measures (absenteeism and suspensions) and all four

Table 2. Pairwise Correlations Between SEL and Observable Behavioral Measures.

	Self-Management	Social Awareness	Self-Efficacy	Growth Mindset	Full-day Absences	Part-day Absences	Suspensions
Self-Management	1						
Social Awareness	.2398**	1					
Self-Efficacy	.4460**	.3298**	1				
Growth Mindset	.5335**	.1953**	.3890*	1			
Full-day Absences	−.1529**	−.0693**	−.0844**	−.0637	1		
Part-day Absences	−.3185**	−.1285**	−.1694**	−.1461**	.4478**	1	
Suspensions	−.0997**	−.0457**	−.0363**	−.0793**	.1481**	.2532**	1

Note. Pairwise correlations.

*$p < .05$. **$p < .01$.

SEL constructs. Most of these correlations are fairly small, with the most notable one between self-management and part-day absenteeism ($p = -.32$). This aligns with prior findings by Kanopka et al. (2020) and Claro and Loeb (2019), and suggests that for the analytic sample being studied in our paper, these two sets of metrics overlap somewhat on the underlying noncognitive skills that they aim to capture.

We also conduct both exploratory and confirmatory factor analyses to examine whether there is evidence to support a single underlying latent variable that explains the relationship among the two sets of measures. Our results indicate that while a two-factor model (the four SEL factors loading on one factor, the three academic behaviors on the second factor) shows better model fit than a unidimensional model, there is a strong (−0.40) correlation among the two factors, indicating some shared source of variance.

Methods

We estimate linear probability models for each of our three long-run outcomes to compare the predictive validity of academic behaviors and SEL measures. Specifically, we model student i in school s and cohort c's education attainment Y_{isc} as a function of students' SEL skills (SEL_i), academic behaviors ($Behavior_i$), demographics and ninth grade GPA (X_i), school fixed effects (θ_s), cohort fixed effects (φ_c), and an idiosyncratic error (c_{isc}):

$$\mathrm{Y}_{\mathrm{isc}} = \sum_{m \in M} \beta_m SEL_{isc,m} + \sum_{n \in N} \beta_n Behavior_{isc,n} + \beta 1 X_{isc} + \theta_{\mathrm{s}} + \varphi_{\mathrm{c}} + \in_{isc}, \quad (1)$$

Across all our specifications, we always include student-level demographic data, including student race/ethnicity, gender, special education status, gifted status, English Learner status, ninth grade GPA, and the neighborhood characteristics of the student's residential census tract (including unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition); school fixed effects; and cohort fixed effects, as baseline controls. In our initial models, we introduce measures of SEL skills and academic behaviors separately, before including the metrics simultaneously in a singular model. In this way, we are able to compare how different sets of noncognitive skill measures change the model's predictive power.

We gage the extent to which a set of noncognitive skills measures change a model's predictiveness in two different ways. First following Jackson et al. (2020), we use V ar(Fˆ), the predicted variance of the predictable impact of a set of noncognitive skills based on the linear relationship between the noncognitive skills for a student and her educational attainment. For example, when estimating the predictive validity of SEL skills on long-term outcomes, we estimate Equation 1 and then compute $\hat{F} = m \in M\ \hat{\beta} mSELisc,m$. Then, by comparing the explained variance across models that include only SEL measures, only academic behaviors, and both of them, we can assess the relative predictive power between the two sets of noncognitive metrics on various long-run outcomes.

The second metric we use to gage predictive validity is the adjusted R-squared value, the corrected goodness-of-fit measure for linear models after accounting for the number of independent variables. We expect the two methods will result in similar conclusions, but the added value of this second metric is the ability to also report the adjusted R-squared for a model with only baseline controls in Equation 1. This facilitates our evaluation of various models with additional sets of noncognitive skills and the extent to which adding an additional set helps improve the explanatory power of the baseline model.

Main Results

Table 3 reports our main findings. For each of the three long-term outcomes, we report results from regressions that first use only ninth grade self-reported SEL skills and academic behaviors as predictors separately, and then a third model that combines both sets of measures. Below, we first focus on comparing the collective predictive power of each set of noncognitive skill measures before we interpret coefficients on individual variables. As mentioned, while sample size ranges from 5,752 to 5,754 for the first two outcomes of interest, the sample size decreases to 2,871 to 2,872 when examining our third outcome of interest (i.e., persistence in second year of college) due to lack of data on this for the younger cohort.

Collective Predictive Power

As discussed in Section 4, we primarily use the predicted variance $\hat{F}$ for self-reported SEL skills and academic behaviors on a particular outcome to compare their predictive power.

Figure 1 presents $\hat{F}$ across different models and outcomes visually. We also use the adjusted R-squared to corroborate and supplement the findings. First, the *SD* of the predicted variance is much higher for academic behaviors than self-reported SEL skills, regardless which long-run outcome we use. The difference is the biggest for high school graduation. Specifically, the *SD* of the predicted effects has a value of 0.103 when using academic

Table 3. Main Results: Predictive Power of SEL Skills and Academic Behaviors.

	On-Time High School Graduation			Immediate College Attendance			Persistence in Second Year of College		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SEL Skills									
Self-Management	0.011		0.005	0.013+		0.008	0.014		0.012
	(0.008)		(0.007)	(0.007)		(0.005)	(0.009)		(0.007)
Growth Mindset	0.002		0.005	−0.005		−0.003	−0.007		−0.006
	(0.005)		(0.005)	(0.006)		(0.006)	(0.009)		(0.009)
Self-Efficacy	−0.008+		−0.003	0.008		0.012+	−0.003		0.000
	(0.004)		(0.004)	(0.007)		(0.006)	(0.010)		(0.009)
Social Awareness	0.006		0.006	0.007		0.007	0.007		0.007
	(0.005)		(0.005)	(0.005)		(0.005)	(0.010)		(0.009)
Academic Behaviors									
Number of Suspensions		−0.011	−0.010		−0.003	−0.003		0.008	0.008
		(0.009)	(0.009)		(0.007)	(0.006)		(0.005)	(0.005)
Full-day Absences		−0.074**	−0.075**		−0.035**	−0.036**		−0.016	−0.017
		(0.014)	(0.014)		(0.012)	(0.012)		(0.021)	(0.020)
Part-day Absences		−0.087**	−0.086**		−0.072**	−0.070**		−0.032+	−0.031+
N	5,754	5,752	5,752	5,754	5,752	5,752	2,872	2,871	2,871
$p\ (F < f)$	.147	.000	.000	.008	.000	.000	.089	.129	.017
SD of predicted effects	0.014	0.103	0.106	0.022	0.071	0.079	0.017	0.030	0.037
Adjusted R^2	.199	.248	.249	.251	.261	.262	.322	.323	.323
Baseline adjusted R^2		.197			.249			.322	

Note. Each column reports coefficients from a separate regression model. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics which include unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition. Baseline adjusted R-squared from models with the independent variables described above without any SEL skills or academic behaviors. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses.

$^{+}p < .10$. $^{**}p < .01$.

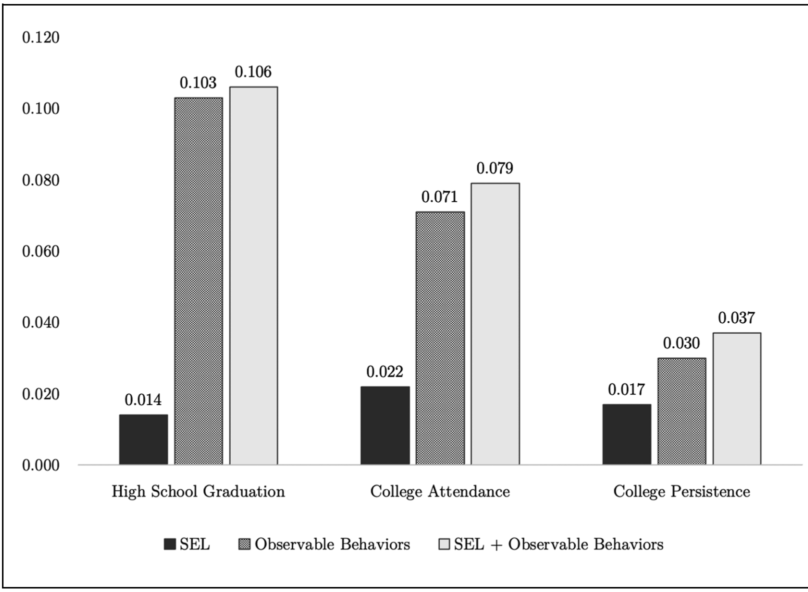

Figure 1. Standard deviation (*SD*) of predicted effects from SEL and/or academic behaviors.

Note. Each *SD* is derived from separate regression models predicting each of the three dependent variables of interest. Covariates include student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA, neighborhood characteristics of the student's residential census tract (unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition), school fixed effects, and cohort fixed effects. College attendance is measured as a binary indicator that equals one if the individual attends a postsecondary institution within 2 years of high school graduation. Persistence is measured as a binary indicator that equals one if the individual attends a postsecondary institution for two consecutive years.

behaviors, more than sevenfolds larger than that when using self-reported SEL (0.014). This contrast is not as strong for postsecondary outcomes, but academic behaviors still exhibit predictive power two to three times larger than SEL skills.

Second, the predictive power of academic behaviors shrink dramatically when we gradually move to more distant outcomes for student attainment. The pattern is different for SEL skills. Although still much lower than academic behaviors, SEL skills' predictive power is slightly more predictive for postsecondary outcomes than high school graduation. Importantly, taken as a whole, the contribution of measures on noncognitive skill to predicting postsecondary outcomes is minimal, especially on college persistence. This is most clearly demonstrated by looking at the adjusted R-squared. Relative to a baseline model that uses student demographics and GPA to predict college persistence, models with academic behaviors, SEL skills, or both, show almost identical values for the adjusted *R*-squared.

Third, across the three outcomes, combining both sets of measures into one model only increases the collective predictive power marginally compared to a model with just academic behaviors. Together, these findings suggest that if the goal is to improve the overall predictive power on student education attainment, SEL skills provide little value over academic behaviors, and academic behaviors are much more predictive for more proximal outcomes than distant ones, such as college persistence.

Predictive Validity of Individual Measures

Table 2 presents our main findings when iteratively adding each set of noncognitive skills to models predicting high school graduation, college attendance, and college persistence. While this is not a causal analysis, model coefficients on individual SEL or behavioral variables can help us understand which measures are driving the collective predictive power we have observed so far.

First, we observe that the point estimates on individual variables are similar in magnitude and significance levels in the combined models containing all noncognitive measures (Table 3, Columns (3), (6), and (9)) as in the respective models containing just one set of noncognitive skills. This is not surprising, given that the correlations between self-reported SEL skills and academic behaviors reported in Table 2 were at best modest in magnitude. If anything, the correlations between SEL skills and academic behaviors should be even smaller compared to those reported in Table 2, as potential unobservable factors that may manifest in correlations between two sets of noncognitive skill measures may be accounted for by our baseline controls for student characteristics and fixed effects.

Additionally, we observe that individual self-reported SEL measures show little to no significant correlation with all three long-run outcomes, on average. While self-management and self-efficacy appear to be marginally correlated with college attendance, the magnitude of the coefficients are small.

Because the four SEL constructs measures are somewhat correlated with each other, we also predict each outcome using each individual SEL construct separately, conditional on student demographics and achievement. This allows us to build parsimonious models that avoid loading potentially collinear constructs into the same model. As shown in Appendix

Table A1, we find that self-management is positively associated with college attendance and persistence, and that self-efficacy and social-awareness both predict college attendance. This suggests that some SEL constructs, especially self-management, may be associated with boosting postsecondary success, but that SEL skills are less correlated with one's ability to successfully complete high school graduation requirements.

Generally, we find that academic behaviors exhibit much stronger predictive power on long-run outcomes relative to SEL skills, with several nuances. First, we find that while the number of suspensions is negatively correlated with two of the three long-run outcomes, the associations are not considered statistically significant (Table 3). However, both absenteeism measures show sizable, negative, and statistically significant coefficients for both high school graduation and immediate college enrollment, regardless of when they are included in a model with or without SEL constructs. These coefficients show diminishing magnitudes and significance levels as we consider more distant post-secondary outcomes such as persistence. Notably, the coefficients on part-day absences are always larger in magnitude relative to those of full-day absences. For the two post-secondary outcomes, this contrast is even stronger, with coefficients on part-day absences almost double the size of the coefficients on full-day absences. This suggests that more granular measures of academic behaviors, which might already exist in existing school administrative data systems, can provide more useful information about student future academic trajectories that is currently not captured by more crude, commonly used measures such as full-day absences or suspensions.

Heterogeneity by Achievement

While we find importance nuances on the predictive power of SEL skills and observable academic behaviors in our analytic sample overall, we recognize that the same noncognitive skill measure might not be equally predictive for students across the achievement distribution.[5]

There are two reasons for this. First, evidence suggests that students of different levels of academic achievement also have different average levels of noncognitive skills. Low-achieving students are more likely to be chronically absent and to accrue behavioral infractions relative to their high-achieving peers (Marchbanks III et al., 2015; Balfanz & Byrnes, 2012). In contrast, high-achieving students miss fewer school days and are much less likely to be suspended. This could be due to skills that are typically unobservable in the relationship between behaviors and academic performance, such as having stronger SEL skills. Second, longer-run outcomes matter in different ways for students at various points of the achievement distribution. Students who are high-achieving in high school are much more likely to graduate and to aim for higher postsecondary outcomes; therefore, there could exist a ''ceiling'' effect on how much additional predictive power the noncognitive skill measures can add. Lower-achieving students may find high school graduation in and of itself a critical milestone.

To investigate heterogeneity, we replicate the analysis separately for a sample of students with GPAs below 2.0 and a sample of students with GPAs of 3.0 and higher, and present these results in Table 4. We again focus on observations of collective predictive power first by visualizing the *SD* of predicted variances in Figure 2.

The most salient finding among low-achieving students (n = 652) is that academic behaviors are extremely predictive of their likelihood of graduating high school: The *SD* of the predicted variance for academic behaviors is one order of magnitude larger compared to the counterpart for SEL skills (0.141vs. 0.024), and more than three times larger compared to that of their high-achieving peers (0.141vs. 0.045). However, when examining models predicting postsecondary outcomes, we find that the contrast between academic behaviors and SEL skills for low-achieving students shrinks close to zero. In other words, academic behaviors are much better predictors than SEL skills of low-achieving students' high school graduation, but are just as powerful (or less powerful, in some models) in predicting these students' college attainment ability. Nonetheless, we observe that the *SD* of the predicted variance in SEL skills for low-achieving students is about 50% larger when predicting post-secondary outcomes than high school graduation, suggesting that the skills and dispositions captured by SEL skills might play a bigger role for these students' postsecondary success.

Somewhat surprisingly, academic behaviors are always two to four times more predictive than SEL skills across all long-run outcomes for the high-achieving student sample (n = 3922). For instance, when predicting likelihood of high school graduation, the *SD* of the predicted variance in a model containing just attendance and suspension measures is 0.045 compared to 0.010 in a model containing just SEL skills.

Third, we observe that the comparative predictive power of observable academic behaviors varies across student subgroups depending on the long-run outcome of interest. For example, observable academic behaviors serve as stronger predictors of high school graduation for low-achieving students than it does for high-achieving students, but they are *weaker* predictors of postsecondary outcomes for low-achieving students relative to the same for high-achieving students. This is a departure from the pattern observed in models containing SEL skills, where the *SD*s of the predicted variance are

Table 4. Predictive Power of SEL Skills and Academic Behaviors, by GPA Subgroups.

	On-Time High School Graduation				Immediate College Attendance				Persistence in Second Year of College			
	GPA $<$ 2 GPA $\geq$ 3				GPA $<$ 2 GPA $\geq$ 3				GPA $<$ 2 GPA $\geq$ 3			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SEL Skills												
Self-Management	0.027		0.006		0.024		0.013		−0.004		0.014	
	(0.023)		(0.005)		(0.017)		(0.009)		(0.020)		(0.014)	
Growth Mindset	0.007		−0.006		−0.024		−0.004		−0.016		−0.008	
	(0.019)		(0.004)		(0.015)		(0.007)		(0.021)		(0.010)	
Self-Efficacy	−0.004		0.000		0.031+		0.005		0.040+		−0.013+	
	(0.020)		(0.006)		(0.017)		(0.010)		(0.022)		(0.007)	
Social Awareness	−0.017		0.005		−0.022		0.009		−0.014		0.024+	
	(0.021)		(0.004)		(0.017)		(0.007)		(0.022)		(0.012)	
Academic Behaviors												
Number of Suspensions		0.003		−0.033		−0.000		−0.038		0.007		−0.039
		(0.013)		(0.035)		(0.009)		(0.052)		(0.005)		(0.055)
Full-day Absences		−0.057**		−0.076**		−0.016		−0.110**		0.008		−0.115**
		(0.019)		(0.024)		(0.016)		(0.029)		(0.009)		(0.038)
Part-day Absences		−0.078**		−0.071**		−0.027+		−0.115**		0.006		−0.135**
		(0.017)		(0.021)		(0.015)		(0.020)		(0.018)		(0.029)
N	652	652	3,922	3,921	652	652	3,922	3,921	384	384	1,914	1,914
p ($F < f$)	.764	.000	.092	.000	.206	.237	.115	.000	.347	.514	.006	.000
SD (predicted SEL/behavior)	0.024	0.141	0.010	0.045	0.040	0.045	0.022	0.070	0.036	0.021	0.030	0.064
Adjusted R^2	.125	.184	.078	.103	.031	.029	.072	.093	.067	.062	.120	.135
Baseline adjusted R^2	.132		.073		.025		.070		.068		.118	

Note. Each column reports coefficients from a separate regression model. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics which include unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition. Baseline adjusted R-squared from models with the independent variables described above without any SEL skills or academic behaviors. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses.

$^{+}p < .10$. $^{**}p < .01$.

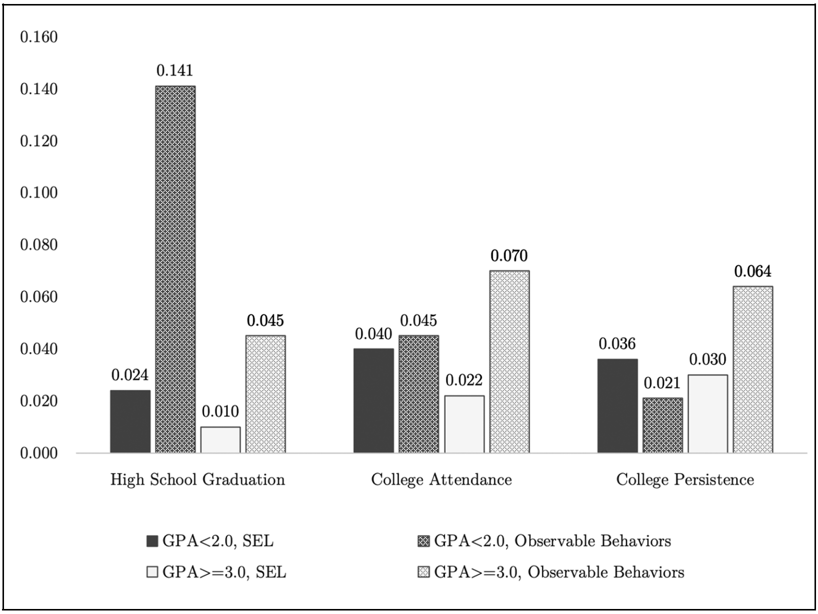

Figure 2. Standard deviation of predicted effects from SEL or academic behaviors, by achievement-specific subgroups.

Note. Each *SD* is derived from separate regression models predicting each of the three dependent variables, separately by achievement-specific subgroups (GPA $<$ 2 and GPA $\geq$ 3). Models predicting outcomes using both SEL and academic behaviors are omitted from display. Covariates include student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA, neighborhood characteristics of the student's residential census tract (unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition), school fixed effects, and cohort fixed effects. College attendance is measured as a binary indicator that equals one if the individual attends a postsecondary institution within 2 years of high school graduation. Persistence is measured as a binary indicator that equals one if the individual attends a postsecondary institution for two consecutive years.

close together in range (between 0.01 and 0.04) regardless of the outcome or achievement-based subgroup of interest.

At the level of individual measures, we again find that absenteeism is far and away the strongest predictor among all noncognitive skill measures for most models, with a few exceptions. Among high-achieving students, absenteeism measures exhibit consistently negative and significant coefficients when predicting any of the three outcomes. This, alongside the considerably large magnitude of the coefficients, suggests that absenteeism is more strongly associated with these milestones relative to suspensions or SEL skills. On the other hand, although full- and part-day absences are predictive of the likelihood of high school graduation among low-achieving students, there is no longer a significant association when examining postsecondary attainment. Given the low adjusted R^2 values in these models, it is feasible that other unobservable factors better predict postsecondary attainment for this particular group of students.

Conclusion

Cultivating student skills and capacities beyond academic achievement is becoming an increasing priority in education policymaking. However, systematic data collection on such skills and capacities in school systems is complicated by conceptual ambiguities, measurement challenges and resource constraints. In this study, we attempt to provide some guidance on this question by comparing the predictive validity of two sets of most widely used metrics on noncognitive factors–observable academic behaviors and student self-reported SEL skills– for high school graduation and postsecondary attainment. To our knowledge, this study is the first that we know of to compare the predictive validity of both academic behaviors and SEL skills concurrently. Using highly detailed administrative data on two cohorts of ninth graders from a large and diverse urban school district, we advance the prior literature by considering more nuanced academic behaviors, using multiple proximal and distal outcomes on educational attainment, and evaluating heterogeneity by student subgroups of interest.

Our findings consistently show much stronger predictive power of academic behaviors than SEL skills across the three outcomes we consider. Specifically, the *SD* of predicted variance of academic behaviors is sevenfolds larger relative to SEL skills for high school graduation, and two to three times larger for college attendance and persistence. Adding SEL skills to a model with academic behaviors add little value to improve the percentage of variance explained for each outcome. At the level of individual measures, we find that part-day absenteeism, a more nuanced measure that captures student class-skipping behavior, demonstrates even stronger predictive power above and beyond full-day absenteeism, a more commonly used metric in school systems. While self-management and self-efficacy show some positive correlations with the outcomes we use, they are small and inconsistent. Importantly, our heterogeneity analysis suggests that academic behaviors are far more important than SEL skills for low-achieving students to graduate high school, SEL skills are more important for them to attend and persist in college.

This research also has several limitations. First, similar to other studies, an inherent weakness of using student self-reported SEL skills is that measurement errors can prevent us from drawing the right conclusion (e.g., West et al., 2016; Duckworth & Yeager, 2015). It is possible that SEL skills might be more predictive than what we report here if the fundamental issue of reference bias is addressed. Second, we use a predictive framework to compare different metrics of noncognitive factors, which prevents us from drawing any causal conclusions. The ability to compare the causal effects of each noncognitive factor on important student outcomes is critical if the goal is to evaluate which skill or behavior schools should cultivate and invest on. Third, a fast-growing literature documents how racial bias and other environmental factors can affect the academic behaviors we use here, especially suspensions. These complexities limit our ability to draw concrete conclusions on whether it is the underlying noncognitive skills academic behaviors capture that are predicting higher education attainment. Lastly, predicting student risks or success is simply one potential use of these measures. Noncognitive measures are also used to monitor student well-being across time, evaluate the impacts of SEL interventions, and identify students for additional supports. While our findings suggest that academic behaviors have some clear advantages over self-reported SEL skills in a predictive framework, we do not imply that SEL skills are less important than academic behaviors, nor do we argue that practitioners should stop their efforts in measuring and promoting student SEL skills. Future studies should go beyond this approach and consider other applications to enrich the discussion on how to best use the various noncognitive factors for policymaking.

Nonetheless, our study points to several likely fruitful directions in research and practice. In particular, our findings start to unveil the untapped potential of developing more fine-grained behavioral measures, which are already being collected by school administrative data systems. For example, adding partial-day absenteeism measures into EWI systems might be particularly fruitful in improving the precision of identifying students at higher risks of dropping out. Given how strongly partial-day absenteeism predicts long-run outcomes, it should be tracked and monitored more closely than what current policy dictates, especially at a time when increased absenteeism is impeding learning recovery from the COVID-19 pandemic (Dee, 2023). Many other academic behaviors, such as tardiness, office discipline referrals, and participation in extracurricular activities, are also relatively easy to measure, potentially contain rich information about students, but have not been well studied in the literature. Also, our heterogeneity results suggest targeted support on certain noncogntive factors for student subgroups might be more productive compared with a more uniformed approach. Our hope is this study will spark more scholarly efforts to build more coherent frameworks for noncognitive factors and their use in school systems.

Appendix A

Table A1. Regressions Using Individual Noncognitive Skill Measures as Predictors.

	(1) High School Graduation	(2) Immediate College Attendance	(3) in second Year of College
SEL Skills			
Self-Management	0.011	0.019**	0.015*
	(0.008)	(0.006)	(0.006)
Growth Mindset	0.003	−0.000	−0.005
	(0.005)	(0.006)	(0.009)
Self-Efficacy	−0.001	0.014*	0.003
	(0.006)	(0.007)	(0.009)
Social Awareness	0.008	0.015**	0.010
	(0.006)	(0.004)	(0.006)
Academic Behaviors			
Number of Suspensions	−0.012*	−0.004	0.006*
	(0.006)	(0.005)	(0.003)
Full-day Absences	−0.082**	−0.039**	0.003
	(0.009)	(0.008)	(0.010)
Part-day Absences	−0.091**	−0.062**	−0.019
	(0.007)	(0.009)	(0.012)
Mean Outcome	0.879	0.679	0.655

Note. Each cell is derived from a separate regression model predicting each dependent variable of interest with a single SEL skill or observable behavior as a predictor. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics which include unemployment rates, poverty rates, percentage of people with a bachelor degree, and racial/ethnic composition. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses.

*$p < .05$. **$p < .01$.

Table A2. Predictive Power of SEL & Observable Behavioral Measures on High School Graduation by Race/Ethnicity.

	Asian		Black		Hispanic		Other		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. SEL Skills										
Self-Management	0.006		−0.000		0.031 +		0.022		0.014	
	(0.008)		(0.020)		(0.015)		(0.028)		(0.022)	
Growth Mindset	−0.005		0.034		0.007		−0.014		−0.026	
	(0.004)		(0.026)		(0.012)		(0.022)		(0.015)	
Self-Efficacy	−0.006		0.025		−0.024+		−0.007		0.009	
	(0.006)		(0.029)		(0.013)		(0.031)		(0.022)	
Social Awareness	0.004		−0.009		0.002		0.003		0.017	
	(0.005)		(0.030)		(0.012)		(0.024)		(0.020)	
B. academic behaviors										
Number of Suspensions		−0.065*		−0.001		−0.029*		−0.002		0.029
		(0.031)		(0.009)		(0.013)		(0.026)		(0.023)
Full-day Absences		−0.103**		−0.092**		−0.067**		−0.157**		−0.056
		(0.027)		(0.027)		(0.019)		(0.048)		(0.050)
Part-day Absences		−0.050**		−0.132**		−0.079**		−0.024		−0.083*
		(0.015)		(0.024)		(0.017)		(0.033)		(0.040)
p ($F < f$)	.485	.000	.091	.000	.238	.000	.766	.000	.026	.037
SD (SEL and behavior)	0.009	0.059	0.047	0.203	0.031	0.116	0.024	0.111	0.035	0.073
Adjusted R^2	.079	.124	.105	.210	.213	.254	.141	.202	.195	.220
Mean outcome	0.950		0.688		0.773		0.849		0.879	
N	2,878		346		1,309		278		513	

Note. Each column reports coefficients from a separate regression model. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics. Baseline adjusted R-squared from models with the independent variables described above without any SEL skills or academic behaviors. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses.

$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Table A3. Predictive Power of SEL & Observable Behavioral Measures on College Attendance, by Race/Ethnicity.

	Asian		Black		Hispanic		Other		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. SEL Skills										
Self-Management	0.006		0.011		0.030**		0.001		0.004	
	(0.010)		(0.017)		(0.010)		(0.032)		(0.030)	
Growth Mindset	−0.003		0.008		0.006		−0.035		0.015	
	(0.008)		(0.020)		(0.014)		(0.024)		(0.027)	
Self-Efficacy	0.045**		0.027		0.004		0.049		−0.008	
	(0.011)		(0.018)		(0.009)		(0.033)		(0.022)	
Social Awareness	−0.008		0.024		–0.001		−0.006		0.026	
	(0.009)		(0.026)		(0.010)		(0.032)		(0.024)	
B. Academic Behaviors										
Number of Suspensions		−0.046+		0.003		0.009		0.063		0.021*
		(0.025)		(0.005)		(0.009)		(0.040)		(0.008)
Full-day Absences		−0.119**		0.006		−0.001		−0.034		−0.056
		(0.033)		(0.019)		(0.015)		(0.039)		(0.051)
Part-day Absences		−0.012		−0.021		−0.035**		−0.005		−0.035
		(0.035)		(0.018)		(0.011)		(0.030)		(0.032)
$p\ (F < f)$	.002	.000	.029	.718	.022	.026	.398	.345	.353	.039
SD (SEL and behavior)	0.044	0.052	0.053	0.022	0.033	0.034	0.049	0.047	0.032	0.046
Adjusted R^2	.180	.181	.244	.230	.252	.251	.251	.253	.234	.237
Mean Outcome	0.612		0.194		0.266		0.421		0.561	
N	2,878		346		1,309		278		513	

Note. Each column reports coefficients from a separate regression model. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics. Baseline adjusted R-squared from models with the independent variables described above without any SEL skills or academic behaviors. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses.

$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Table A4. Predictive Power of SEL & Observable Behavioral Measures on Persistence, by Race/Ethnicity.

	Asian		Black		Hispanic		Other		White	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. SEL Skills										
Self-Management	0.010		−0.003		0.009		0.014		−0.029	
	(0.009)		(0.013)		(0.007)		(0.021)		(0.019)	
Growth Mindset	−0.003		−0.018		0.002		−0.037		0.027	
	(0.006)		(0.012)		(0.008)		(0.029)		(0.018)	
Self-Efficacy	0.016*		0.027*		0.013**		0.048*		−0.007	
	(0.007)		(0.011)		(0.005)		(0.023)		(0.015)	
Social Awareness	−0.000		0.004		−0.015		−0.009		0.041**	
	(0.004)		(0.017)		(0.009)		(0.012)		(0.014)	
B. Academic Behaviors										
Number of Suspensions		−0.002		0.003		0.004		0.003		−0.000
		(0.037)		(0.002)		(0.006)		(0.020)		(0.011)
Full-day Absences		−0.042		0.005		0.001		0.010		−0.019
		(0.029)		(0.0121)		(0.009)		(0.029)		(0.027)
Part-day Absences		−0.011		−0.015		−0.007		0.032		0.003
		(0.015)		(0.010)		(0.005)		(0.022)		(0.024)
p ($F < f$)	.100	.210	.036	.404	.080	.573	.250	.456	.003	.901
SD (SEL and behavior)	0.022	0.020	0.027	0.016	0.017	0.006	0.053	0.034	0.044	0.009
Adjusted R^2	.461	.461	.138	.132	.228	.226	.379	.371	.475	.466
Mean Outcome	0.302		0.066		0.105		0.205			0.267
N	1,499		171		622		135			254

Note. Each column reports coefficients from a separate regression model. All measures for SEL skills and academic behaviors are standardized. All models control for student gender, race/ethnicity, gifted status, special education status, English Learner status, ninth grade GPA and neighborhood characteristics. Baseline adjusted R-squared from models with the independent variables described above without any SEL skills or academic behaviors. All models also control for school and cohort fixed effects. Standard errors are clustered at the school-by-cohort level and reported in parentheses. Sample only includes initial year of ninth grade cohorts.

*$p < .05$. **$p < .01$.

Appendix B

Student SEL Skills Survey Items

Self-Management

Please answer how often you did the following during the past 30 days. During the past 30 days.

(Almost Never, Once in a While, Sometimes, Often, Almost All the Time)

1. I came to class prepared.
2. I remembered and followed directions.
3. I got my work done right away instead of waiting until the last minute.
4. I paid attention, even when there were distractions.
5. I stayed calm even when others bothered or criticized me.

Growth Mindset

In this section, please think about your learning in general. Please indicate how true each of the following statements is for you:

(Not At All True, A Little True, Somewhat True, Mostly True, Completely True)

1. I can change my intelligence with hard work.
2. I can increase my intelligence by challenging myself.
3. I am capable of learning anything.
4. I can do well in a subject even if I am not naturally good at it.

Self-Efficacy

How confident are you about the following (either at school or online)?

(Not At All Confident, A Little Confident, Somewhat Confident, Mostly Confident, Completely Confident)

1. I can earn an A in my classes.
2. I can do well on all my tests, even when they're difficult.
3. I can master the hardest topics in my classes.
4. I can meet all the learning goals my teachers set.

Social Awareness

In this section, please help us better understand your thoughts and actions when you are with other people in person or online. Please answer how often you did the following during the past 30 days. During the past 30 days. . .

1. How carefully did you listen to other people's points of view? (Not Carefully At All, Slightly Carefully, Somewhat Carefully, Quite Carefully, Extremely Carefully)
2. How often did you compliment others' accomplishments? (Almost Never, Once in a while, Sometimes, Often, Almost all the time)
3. How well did you get along with students who are different from you? (Did Not Get Along At All, Got Along A Little Bit, Got Along Somewhat, Got Along Pretty Well, Got Along Extremely Well)
4. How clearly were you able to describe your feelings? (Not At All Clearly, Slightly Clearly, Somewhat Clearly, Quite Clearly, Extremely Clearly)
5. When others disagreed with you, how respectful were you of their views? (Not At All Respectful, Slightly Respectful, Somewhat Respectful, Quite Respectful, Extremely Respectful)

Acknowledgment

The authors thank Jim Soland, Marcia Davis, and participants in APPAM and SREE annual conferences for helpful comments and discussions. The data were provided via in-kind support from a local educational agency using a data sharing agreement that requires agency review of the findings of the research prior to publication. Opinions reflect those of the authors and not necessarily those of the funding agencies or the data-sharing partner.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Jing Liu https://orcid.org/0000-0002-9918-8642

Notes

1. There are eight districts in the CORE partnership, including Fresno, Long Beach, Los Angeles, Oakland, San Francisco, and Santa Ana, Sacramento City, and Garden Grove Unified School Districts.

2. The CORE districts convened SEL experts and representatives from each of the CORE districts to discuss and vote for which SEL competency to be included. For more details about this decision process, see Krachman et al., 2016.
3. We also produced scores using IRT methods. Because the correlation between the IRT scores and our standardized scores is extremely high at approximately .95, we present the standardized scores in our analysis.
4. We do not know the rate of persistence for the 2016 cohort as our district partner has not yet made NSC data available for school year 2020 to 2021. We code this variable as missing for the latter cohort and only use data for the 2015 cohort when using college persistence as the outcome variable.
5. We also conduct heterogeneity analysis by student race/ethnicity subgroups, but certain racial groups have too small a sample size that prevents us from drawing precise estimates. We report these estimates in Appendix Tables A2, A3, and A4 but do not discuss them in the main text.

References

Allensworth, E. (2013). The use of ninth-grade early warning indicators to improve chicago schools. *Journal of Education for Students Placed at Risk (JESPAR)*, *18*(1), 68–83.

Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. (2011). Personalitypsychology and economics. In E. A. Hanushek, S. Machin, and L. Woessmann (Eds.), *Handbook of the economics of education* (*Vol. 4*, pp. 1–181). Elsevier.

Bacher-Hicks, A., Billings, S. B., & Deming, D. J. (2019). *The school to prison pipeline: Long-run impacts of school suspensions on adult crime* (Tech. Rep.). National Bureau of Economic Research.

Balfanz, R., & Byrnes, V. (2012). The importance of being in school: A report on absenteeism in the nation's public schools. *The Education Digest*, *78*(2), 4.

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early Identification and effective interventions. *Educational Psychologist*, *42*(4), 223–235.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, *28*(2), 117–148. https://doi.org/10.1207/s15326985ep2802_3

Barrett, N., McEachin, A., Mills, J. N., & Valant, J. (2021). Disparities and discrimination in student discipline by race and family income. *The Journal of Human Resources*, *56*, 711–748.

Belfield, C., Bowden, A. B., Klapp, A., Levin, H., Shand, R., & Zander, S. (2015). The economic value of social and emotional learning. *Journal of Benefit-Cost Analysis*, *6*(3), 508–544.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development*, *78*(1), 246–263.

Brown, J. L., Jones, S. M., LaRusso, M. D., & Aber, J. L. (2010). Improving classroom quality: Teacher influences and experimental impacts of the 4rs program. *Journal of Educational Psychology*, *102*(1), 153–167.

Chetty, R., Friedman, J. N., Hilger, N., Saez, E., Schanzenbach, D. W., & Yagan, D. (2011). How does your kindergarten classroom affect your earnings? Evidence from project star. *The Quarterly Journal of Economics*, *126*(4), 1593–1660.

Claro, S., & Loeb, S. (2019). Self-management skills and student achievement gains: Evidence from california's core districts. *EdWorking Paper*, *19*(138), 1–35.

Core Districts. (2021). Social-emotional & culture-climate domain – social emotional skills. https://coredistricts.org/wp-content/uploads/2021/01/ SEL-Metrics-update 1.5.21.pdf

Council, N. R., et al. (2012). *Education for life and work: Developing transferable knowledge and skills in the 21st century*. National Academies Press.

Cunha, F., Heckman, J., & Schennach, S. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrics*, *78*(3), 883–931.

Cunningham, W. V., & Villaseñor, P. (2016). Employer voices, employer demands, and implications for public skills development policy connecting the labor and education sectors. *The World Bank Research Observer*, *31*(1), 102–134.

Davison, M., Penner, A. M., Penner, E. K., Pharris-Ciurej, N., Porter, S. R., Rose, E. K., Shem-Tov, Y., & Yoo, P. (2022). School discipline and racial disparities in early adulthood. *Educational Researcher*, *51*, 231–234.

Dee, T. S. (2023). Higher chronic absenteeism threatens academic recovery from the covid-19 pandemic.

De Laet, S., Colpin, H., Vervoort, E., Doumen, S., Van Leeuwen, K., Goossens, L., & Verschueren, K. (2015). Developmental trajectories of children's behavioral engagement in late elementary school: Both teachers and peers matter. *Developmental Psychology*, *51*(9), 1292–1306.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593–1640.

DePaoli, J. L., Atwell, M. N., & Bridgeland, J. (2017). Ready to lead: A national principal survey on how social and emotional learning can prepare children and transform schools. a report for casel. *Civic Enterprises*.

de Ridder, D. T., Lensvelt-Mulders, G., Finkenauer, C., Stok, F. M., & Baumeister, R. F. (2012). Taking stock of self-control: A meta-analysis of how trait self-control relates to a wide range of behaviors. *Personality and Social Psychology Review*, *16*(1), 76–99.

Duckworth, A. L., & Seligman, M. E. (2005). Self-discipline outdoes IQ in predicting academic performance of adolescents. *Psychological Science*, *16*(12), 939–944. https://doi.org/10.1111/j.1467-9280.2005.01641.x

Duckworth, A. L., & Seligman, M. E. P. (2006). Self-discipline gives girls the edge: Gender in self-discipline, grades, and achievement test scores. *Journal of Educational Psychology*, *98*(1), 198–208.

Duckworth, A. L., & Yeager, D. S. (2015). Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, *44*(4), 237–251. https://doi.org/10.3102/0013189X15584327

Durlak, J. A., Weissberg, R. P., Dymnicki, A. B., Taylor, R. D., & Schellinger, K. B. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based Universal Interventions. *Child Development*, *82*(1), 405–432.

Dweck, C. S., Walton, G. M., & Cohen, G. L. (2014). *Academic tenacity: Mindsets and skills that promote long-term learning. Bill & Melinda Gates Foundation*.

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

Farrington, C. A., Roderick, M., Allensworth, E., Nagaoka, J., Keyes, T. S., Johnson, D. W., & Beechum, N. O. (2012). *Teaching adolescents to become learners: The role of noncognitive factors in shaping school performance–a critical literature review*. ERIC.

Fornander, M. J., & Kearney, C. A. (2019). Family environment variables as predictors of school absenteeism severity at multiple levels: Ensemble and classification and regression tree analysis. *Frontiers in Psychology*, *10*, 2381.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109.

Gilliam, W. S., Maupin, A. N., Reyes, C. R., Accavitti, M., & Shic, F. (2016). *Do early educators' implicit biases regarding sex and race relate to behavior expectations and recommendations of preschool expulsions and suspensions* (*Vol. 9*, pp. 1–16). Yale University Child Study Center.

Gonz'alez, T. (2015). Socializingschools: Addressing racial disparities in discipline through restorative justice. In D. J. Losen (Ed.), *Closing the School Discipline gap: Equitable Remedies for excessive exclusion*. *2014*.

Gregory, A., & Fergus, E. (2017). Social and emotional learning and equity in school discipline. *The Future of Children/Center for the Future of Children, the David and Lucile Packard Foundation*, *27*, 117–136.

Hawkins, J. D., Kosterman, R., Catalano, R. F., Hill, K. G., & Abbott, R. D. (2008). Effects of social development intervention in childhood fifteen years later. *Archives of Pediatrics & Adolescent Medicine*, *162*(12), 1133–1141.

Heckman, J., Stixrud, J., & Urzua, S., S., (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Heckman, J. J., Humphries, J. E., & Kautz, T. (2014). *The myth of achievement tests: The GED and the role of character in American life*. University of Chicago Press.

Heckman, J. J., & Vytlacil, E. (2001). Policy-relevant treatment effects. *The American Economic Review*, *91*(2), 107–111.

Holt, S., & Gershenson, S. (n.d). The impact of teacher demographic representation on student attendance and suspensions.

Hough, H., Kalogrides, D., & Loeb, S. (2017). Using surveys of students' social-emotional learning and school climate for accountability and continuous improvement. Policy Analysis for California Education, PACE.

Humphries, J. E., & Kosse, F. (2017). On the interpretation of non-cognitive skills – What is being measured and why it matters. *Journal of Economic Behavior & Organization*, *136*, 174–185.

Jackson, C. K. (2018). What do test scores miss? The importance of teacher effects on non–test score outcomes. *The Journal of Political Economy*, *126*(5), 2072–2107.

Jackson, C. K., Porter, S. C., Easton, J. Q., Blanchard, A., & Kiguel, S. (2020). School effects on socioemotional development, school-based arrests, and educational attainment. *The American Economic Review*, *2*(4), 491–508.

Jones, D. E., Greenberg, M., & Crowley, M. (2015). Early social-emotional functioning and public health: The relationship between kindergarten social competence and future wellness. *American Journal of Public Health*, *105*(11), 2283–2290.

Jones, S., Bailey, R., Brush, K., & Barnes, S. (2016). *What is the same and what is different? making sense of the "non-cognitive" domain: Helping educators translate research into practice*. Harvard Graduate School of Education. https://easel.gse.harvard.edu/files/gse-easel-lab/files/wordsmatterpaper.pdf

Jones, S. E. A. (2021). *Navigating SEL from the inside out*. Wallace Foundation. https://www.wallacefoundation.org/knowledge-center/Documents/navigating-social-and-emotional-learning-from-the-inside-out-2ed.pdf

Juvonen, J., & Graham, S. (2014). Bullying in schools: The power of bullies and the plight of victims. *Annual Review of Psychology*, *65*, 159–185.

Kanopka, K., Claro, S., Loeb, S., West, M. R., & Fricke, H. (2020). *What do changes in social-emotional learning tell us about changes in academic and behavioral outcomes?*Policy Analysis for California Education.

Krachman, S. B., Arnold, R., & LaRocca, R. (2016). *Expanding the definition of student success: A case study of the core districts*. Transforming Education.

Ladd, G. W., Herald-Brown, S. L., & Reiser, M. (2008). Does chronic classroom peer rejection predict the development of children's classroom participation during the grade school years? *Child Development*, *79*(4), 1001–1015.

Liu, J., Hayes, M. S., & Gershenson, S. (In Press). JUE insight: From referrals to suspensions: New evidence on racial disparities in exclusionary discipline. *Journal of Urban Economics*.

Liu, J., Lee, M., & Gershenson, S. (2021). The short- and long-run impacts of secondary school absences. *Journal of Public Economics*, *199*, 10441.

Lochman, J. E., Coie, J. D., Underwood, M. K., & Terry, R. (1993). Effectiveness of a social relations intervention program for aggressive and nonaggressive, rejected children. *Journal of Consulting and Clinical Psychology*, *61*(6), 1053–1058.

Loeb, S., Christian, M. S., Hough, H., Meyer, R. H., Rice, A. B., & West, M. R. (2019). School differences in social–emotional learning gains: Findings from the first large-scale panel survey of students. *Journal of Educational and Behavioral Statistics*, *44*(5), 507–542.

Marchbanks, M. P., Blake, J. J., Booth, E. A., Carmichael, D., Seibert, A. L., & Fabelo, T. (2015). The economic effects of exclusionary discipline on grade retention and high school dropout. In D. J. Losen (Ed.), *Closing the school discipline gap: Equitable remedies for excessive exclusion* (pp. 59–74). Teachers College, Columbia University.

McNeely, C. A., Nonnemaker, J. M., & Blum, R. W. (2002). Promoting school connectedness: Evidence from the national longitudinal study of adolescent health. *The Journal of School Health*, *72*(4), 138–146.

Messick, S. (1979). Potential uses of noncognitive measurement in education. *Journal of Educational Psychology, 71*(3), 281.

Meyer, R. H., Wang, C., & Rice, A. B. (2018). *Measuring students' social-emotional learning among california's core districts: An IRT modeling approach*. Working paper. Policy Analysis for California Education.

Moffitt, T. E., Arseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., Houts, R., Poulton, R., Roberts, B. W., Ross, S., Sears, M. R., Thomson, W. M., & Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences*, *108*(7), 2693–2698.

Neel, C. G., & Fuligni, A. (2013). A longitudinal study of school belonging and academic motivation across high school. *Child Development*, *84*(2), 678–692.

Osher, D., & Kendziora, K. (2010). Buildingconditions for learning and healthy adolescent development: Strategic approaches. In D. Osher and K. Kendziora (Eds.), *Handbook of youth prevention science* (pp. 121–140). Routledge.

Pas, E. T., & Bradshaw, C. P. (2012). Examining the association between implementation and outcomes. *The Journal of Behavioral Health Services & Research*, *39*(4), 417–433.

Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322–338.

Resnick, M. D., Bearman, P. S., Blum, R. W., Bauman, K. E., Harris, K. M., Jones, J., Tabor, J., Beuhring, T., Sieving, R. E., Shew, M., Ireland, M., Bearinger, L. H., & Udry, J. R. (1997). Protecting adolescents from harm: Findings from the national longitudinal study on adolescent health. *Journal of the American Medical Association*, *278*(10), 823–832.

Revelle, W. (2007). Experimentalapproaches to the study of personality. In R. R. Robins, R. C. Fraley, and R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 37–61). The Guilford Press.

Rumberger, R. W., & Larson, K. A. (1998). Student mobility and the increased risk of high school dropout. *American Journal of Education*, *107*(1), 1–35.

Rushton, J. L., Forcier, M., & Schectman, R. M. (2002). Epidemiology of depressive symptoms in the national longitudinal study of adolescent health. *Journal of the American Academy of Child and Adolescent Psychiatry*, *41*(2), 199–205.

Schanfield, M. R., Chang, H. N., & Osher, D. M. (2019). Chronic absence: A sign to invest in conditions for learning. In J. A. Fredricks, A. L. Reschly and S. L. Christenson (Eds.), *Handbook of student engagement interventions* (pp. 183–198). Elsevier.

Schanzenbach, D. W., Nunn, R., Bauer, L., Mumford, M., & Breitwieser, A. (2016). *Seven facts on noncognitive skills from education to the labor market*. The Hamilton Project.

Segal, C. (2013). Misbehavior, education, and labor market outcomes. *Journal of the European Economic Association*, *11*(4), 743–779.

Soland, J., Jensen, N., Keys, T., Wolk, E., & Bi, S. (2018). *Is low test motivation a sign of disengagement from school? examining indicators of dropout conditional on rapid guessing scores*. Educational Assessment.

Sorensen, L. C., Bushway, S. D., & Gifford, E. J. (2022). Getting tough? The effects of discretionary principal discipline on student outcomes. *Education Finance and Policy*, *17*(2), 255–284.

Taylor, R. D., Oberle, E., Durlak, J. A., & Weissberg, R. P. (2017). Promoting Positive Youth Development through School-Based social and emotional learning interventions: A Meta-Analysis of Follow-Up effects. *Child Development*, *88*(4), 1156–1171.

Vriesema, C. C., & Gehlbach, H. (2021). Assessing survey satisficing: The impact of unmotivated questionnaire responding on data quality. *Educational Researcher*, *50*(9), 618–627.

West, M. R., et al. (2016). Should non-cognitive skills be included in school accountability systems? preliminary evidence from california's core districts. *Evidence Speaks Reports*, *1*(13), 1–7.

West, M. R., Buckley, K., Krachman, S. B., & Bookman, N. (2018). Development and implementation of student social-emotional surveys in the core districts. *Journal of Applied Developmental Psychology*, *55*, 119–129.

Whitney, C. R., & Liu, J. (2017). What we're missing: A descriptive analysis of part-day absenteeism in secondary school. *AERA Open*, *3*(2), 23328584177 03660.

Woods, J. (2018). *50-state comparison: States' school accountability systems*. Education Commission of the States. https://www.ecs.org/50-state-comparison-states-schoolaccountability-systems.

Woodward, H., & Munns, G. (2003). *Insiders' voices: Self-assessment and student engagement* [Conference session]. *New Zealand association for research in education (NZARE) and Australian association for research in education (AARE) joint conference*.

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

Zimmerman, B. J., Bandura, A., & Martinez-Pons, M. (1992). Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting. *American Educational Research Journal*, *29*(3), 663–676.

Author Biographies

JING LIU, PhD, is an assistant professor in education policy at the University of Maryland College Park, 2203 Benjamin Building, College Park, MD 20740, and a research affiliate at the IZA Institute of Labor Economics; *jliu28@umd.edu*. He uses novel tools to understand the causes of education inequality and inform effective policy solutions that will combat inequality and improve educational effectiveness.

MEGAN KUHFELD, PhD, is a research scientist at NWEA, 121 NW Everett Street, Portland, OR 97209; *megan.kuhfeld@nwea.org*. Her research seeks to understand students' academic and social-emotional learning trajectories and the school and neighborhood influences that promote optimal growth.

MONICA G. LEE, PhD, is a senior research associate at Stanford University, Palo Alto, CA 94305; *monica_lee@stanford.edu*. Her research interests include experimental and quasi-experimental methods, absenteeism, and social-emotional learning.