

# Predicting Early Academic Failure in High School From Prior Academic Achievement, Psychosocial Characteristics, and Behavior

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The authors examined the differential effects of prior academic achievement, psychosocial, behavioral, demographic, and school context factors on early high school grade point average (GPA) using a prospective study of 4,660 middle-school students from 24 schools. The findings suggest that (a) prior grades and standardized achievement are the strongest predictors of high school GPA and (b) psychosocial and behavioral factors (e.g., motivation, self-regulation, and social control) add incremental validity to the prediction of GPA. When comparing the relative importance of each set of predictors (the dominance analysis technique), the variance accounted for by psychosocial and behavioral factors is comparable to that accounted for by prior grades. These findings highlight the importance of effective risk assessment based on multiple measures (i.e., academic, psychosocial, and behavioral) for the purpose of identifying risk, referring students to intervention, and improving academic success.

*Keywords:* academic performance, psychosocial and behavioral factors

High academic failure and dropout rates remain significant issues in the United States, with estimates of over 25% of public school students failing to earn a diploma (Education Week, 2009; Stillwell, 2009). In some states and communities, these rates exceed 50% of all entering ninth-grade students. The No Child Left Behind (NCLB) legislation includes systematic monitoring of student academic progress through standardized achievement testing, but this does not ensure the proper identification and intervention of at-risk students. We now know that measuring critical psychosocial factors (PSFs; e.g., motivation, social control, self-regulation) as well as behavioral factors can increase schools' abilities to identify and intervene with students at risk of academic failure and dropout (Zins, Bloodworth, Weissberg, & Walberg, 2004). After reviewing studies of student dropout conducted over the past 25 years, Rumberger and Lim (2008) identified several factors that differentiate students who graduate from those who drop out of high school. Their list includes learning behaviors,

attitudes, demographics, and characteristics of family and school. Similarly, the Baltimore Education Research Consortium (Mac Iver, 2010) found that poor grades and course failure are strong predictors of high school dropout. These findings, among others, point to the importance of understanding psychosocial and behavioral data when assessing risk.

Several single-sample studies have examined the direct and indirect effects of PSFs and behavioral factors on academic success, highlighting a range of constructs, including self-efficacy, motivation, locus of control, attitude toward learning, attention and persistence, as well as strategy and flexibility (Grigorenko et al., 2009; Yen, Konold, & McDermott, 2004). As Grigorenko and others (2009) highlight, self-regulated learning provides incremental validity after controlling for standardized achievement and grade point average (GPA). These findings are consistent with a large-scale review of student success research conducted in elementary and middle school, where social and emotional learning (SEL)<sup>1</sup> constructs—of self- and social awareness, self-management, relationship skills, and responsible decision making—were found to be key antecedents of student academic performance (e.g., Payton et al., 2008).

Analogous results have been obtained during the transition to postsecondary education, where a combination of PSFs, academic performance, and standardized achievement are predictive of first-year college academic success and persistence into the second year (cf. Robbins, Allen, Casillas, Peterson, & Le, 2006). Using an assessment model based on motivational, social control, and self-regulatory factors (see Le, Casillas, Robbins, & Langley, 2005;

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<sup>1</sup>SEL is often used in the literature to describe the same types of constructs referred to as PSFs.

Robbins et al., 2004), academic discipline, social activity, and emotional control made incremental contributions beyond high school GPA and standardized achievement for predicting college academic performance and persistence behavior (Robbins et al., 2006). Similar findings also have been obtained within a graduate education context, where personality and behavioral data provide incremental validity contributions after controlling for college GPA and standardized exams (e.g., Graduate Record Examinations) when predicting graduate school outcomes, such as attrition and time to degree (cf. Kyllonen, Walters, & Kaufman, 2005).

Extending from the previous Talent Development Middle Grades studies, Balfanz and his colleagues (Balfanz, Herzog, & Mac Iver, 2007; Neild, Balfanz, & Herzog, 2007) created an early warning system to identify Grade 6 students who were more likely to drop out in high school. They followed a large cohort of approximately 13,000 students from Grade 6 through 12 and examined students' dropout status 1 year beyond students' expected graduation from high school. They identified five warning flags that are important predictors of dropout: (a) having a final grade of F in math, (b) having a final grade of F in English, (c) attending school 80% of the days or less for the academic year, (d) receiving one or more out-of-school suspensions, and (e) receiving a final unsatisfactory behavior grade in any subject. Results showed that these warning flags together can effectively identify 60% of the students who will not graduate within 1 year of expected graduation, thus showing substantial promise for assisting schools to identify students at academic risk (Balfanz et al., 2007). This research clearly shows that academic performance and behavioral indicators are identifiable during middle school and appear to be effective predictors of future academic difficulties.

Middle school is a critical transition point for the development of later high school and postsecondary success behaviors. In fact, academic achievement at the eighth-grade level has larger effects on college and career readiness than anything assessed in high school (ACT, 2008). Although the importance of psychosocial and behavioral variables for middle-school students' achievement and

persistence has been addressed in some studies (e.g., Dymnicki, 2004; Rumberger & Lim, 2008), our knowledge is limited by the absence of a more comprehensive approach that combines a broader range of measures, including academic achievement, as well as student motivational, social, self-regulatory, and behavioral factors. Furthermore, the use of a large sample and longitudinal design are essential to more clearly examine the effects of each component and to provide a more comprehensive examination of risk assessment and classification.

Thus, the focus of this study was on a comprehensive assessment system with measures of PSFs, behavior, academic achievement, as well as school and demographic factors using a sample of students transitioning from middle to high school. We examine the interplay of the different factors and their effects on academic risk and performance (i.e., GPA) outcomes so as to better understand which students are at greatest risk for academic failure in high school.

### A Comprehensive Assessment System

Table 1 presents a system of measures for predicting middle-school academic risk using a multidimensional theoretical framework. These are divided into five categories: (a) prior academic achievement as measured by course grades and standardized achievement scores; (b) PSFs including multiple measures of motivational, social control, and self-regulatory factors; (c) behavioral indicators including time spent on homework, absenteeism, and number of school moves; (d) school factors including average class size and percentage of students eligible for free/reduced lunch; and (e) demographic factors including gender, race/ethnicity, parental education, home resources, and family educational aspirations. We chose this system based on earlier research on the role of cognitive, psychosocial, and career factors in college success (e.g., Robbins et al., 2006) and the role of motivational, social control, and self-regulatory factors on educational outcomes (see Robbins et al., 2004; Robbins, Oh, Le, & Button, 2009).

Table 1  
*Predictors Included in Assessment System of Middle-School Academic Risk*

Category	Measures		
Academic achievement	<ul style="list-style-type: none"> <li>• school grades</li> <li>• EXPLORE scores</li> </ul>		
	Motivation	Social control	Self-regulation
Psychosocial characteristics	<ul style="list-style-type: none"> <li>• Academic Discipline</li> <li>• Commitment to School</li> <li>• Optimism</li> </ul>	<ul style="list-style-type: none"> <li>• Family Attitude toward Education</li> <li>• Family Involvement</li> <li>• Relationships w/School Personnel</li> <li>• School Safety Climate</li> </ul>	<ul style="list-style-type: none"> <li>• Managing Feelings</li> <li>• Orderly Conduct</li> <li>• Thinking before Acting</li> </ul>
Behavioral indicators	<ul style="list-style-type: none"> <li>• days absent</li> <li>• homework not done</li> <li>• media time</li> </ul>	<ul style="list-style-type: none"> <li>• # of times changed school</li> <li>• time spent on homework</li> </ul>	
School factors	<ul style="list-style-type: none"> <li>• percent free/reduced lunch</li> <li>• percent minority</li> <li>• average class size</li> </ul>		
Demographic factors	<ul style="list-style-type: none"> <li>• gender</li> <li>• race/ethnicity</li> <li>• parental education</li> <li>• home resources</li> <li>• family education aspirations</li> </ul>		

Furthermore, we took a methodological-substantive approach (cf. Marsh & Hau, 2007) by evaluating our assessment system using the dominance analysis technique (Azen & Budescu, 2003), which allowed us to compare the relative importance of each set of predictors in the assessment system without some of the limitations and assumptions required in typical regression approaches.

### Previous Research on the Relationship Between Motivation, Social Control, Self-Regulation, and Behavior

Kanfer and Heggstad (1997, 1999) illustrated the importance of motivation and self-regulation as proximal determinants of goal-oriented behaviors when examining the precursors of learning. Motivation and self-regulation are undergirded by three critical processes: self-monitoring, self-evaluation, and self-reactions (Kanfer & Ackerman, 1989; Kanfer & Heggstad, 1997). These processes are changeable through targeted intervention and reflect students' ability to motivate themselves to achieve via self-regulatory processes (Kuhl, 1985) as observed in study habits and skills. Robbins et al. (2009) include social control as another key mechanism in student success, especially as it relates to persistence behavior. Social control is associated with college persistence (Robbins et al., 2006, 2009) and could also be a mechanism to enhance high school academic success and prevent dropout. Helping students feel connected to their school environment and be able to take advantage of family, peer, and school supports can promote feelings of relatedness or "embeddedness" in an educational environment, which is necessary for continued persistence behavior.

Prior research examining relationships of motivation, social control, self-regulation, and related behaviors with academic performance and persistence are briefly described below.

#### Motivation and Behavior

*Motivation* refers to the self-regulatory mechanism by which individuals act on prescribed behaviors and implement learning activities and/or pursue goals (Robbins et al., 2009). Specifically, weak self-regulation makes meeting goals less likely and reduces learning motivation (Gailliot, Mead, & Baumeister, 2008). A considerable body of research is accumulating to show that motivated and self-regulated learners have better chances to achieve positive academic outcomes (Covington, 2000; Deci, Vallerand, Pelletier, & Ryan, 1991; Dweck, 2000; Pintrich & De Groot, 1990). Although motivation is defined in the educational psychology literature as a self-regulated process, we see it as distinct from the broader construct of self-regulation in that self-regulation is also related to both emotion and behavioral regulation or constraint. Most student dropout studies also indicate that lacking learning motivation can lead to dropout behaviors (Rumberger & Lim, 2008). A recent study by Martin (2009) examining motivation and engagement throughout the life span found that, compared with elementary and college students, students in middle and high school are less likely to be motivated and engaged.

Several studies have examined the development and effects of conscientiousness and motivation (for a thorough review of the term *motivation* and related constructs, see Murphy & Alexander, 2000). For example, based on a 10-year longitudinal study of student personality development from ages 8–10 to late adoles-

cence, Shiner (2000) claimed that the expression of conscientiousness in academic settings (i.e., academic conscientiousness) varies across time and can be improved depending on context. Students with high motivation for learning are more likely to have strong academic skills and achievement because they work harder and choose more stimulating environments. Heckman and Rubinstein's (2001) study of students with GEDs found evidence that GED recipients, despite having higher cognitive abilities than other high school dropouts, showed lower levels of persistence, ability to plan ahead, and ability to adapt to their environment compared with students who had not dropped out. Clearly, motivation appears to be a key mechanism in predicting later academic achievement and persistence at all educational levels, including middle school.

Previous research also has found associations of characteristics like optimism, self-efficacy, and positive self-perceptions of ability to achievement motivation and academic performance where students who express more positive views about themselves, their abilities, and their thoughts about the future earn higher grades than students with more pessimistic views (e.g., Capella & Weinstein, 2001; Dweck, 2002; Lounsbury, Sundstrom, Loveland, & Gibson, 2003; Skinner, Wellborn, & Connell, 1990).

Homework completion is a common grading criterion in daily formative assessment for teachers. Also, we often infer motivation to learn through behaviors such as time spent on homework, rather than on media (e.g., watching TV, surfing the Internet, or playing video games). Students who spend 3 or more hours per week completing school work have a higher likelihood of having positive attitudes toward homework (Xu, 2006). The amount of homework middle-school students complete has a positive association with achievement, although this is not true for elementary students (Cooper, Lindsay, Nye, & Greathouse, 1998). In our assessment system, we use scales designed to measure multiple aspects of motivation described above (i.e., Academic Discipline, Commitment to School, Optimism), as well as homework time.

#### Social Control and Behavior

*Social control* refers to an individual's skills in engaging the social environment in ways that support and reinforce his or her learning activities (Robbins et al., 2009). Attending extracurricular activities, having good relationships with school personnel, and involving parents in school life are examples of demonstrating engaged behaviors in the social environment. In a longitudinal study in which cognitive skills were controlled for, Lleras (2008) argued that high school students with better social skills and more involvement in extracurricular activities have higher academic achievement and earn higher salaries after 10 years. Parent involvement in education, as reflected in academic socialization (e.g., discussing learning strategies with children), also has been shown to improve academic achievement (Hill & Tyson, 2009). Also, in student dropout studies, devoting time and attention to school activities and getting along with teachers and peers showed a reduction in dropout behaviors (Renzulli & Park, 2000; Rumberger & Lim, 2008).

Insufficient social connections might lead to increased absenteeism. Similarly, an increased number of school moves is likely related to poor social connection. Studies show that students with

higher rates of absenteeism and higher rates of school mobility are more likely to drop out of school during middle school or during the transition from middle to high school (Rumberger & Lim, 2008). In both qualitative and quantitative studies, students' self-reported school and neighborhood safety have been associated with academic performance (Bridgeland, Dilulio, & Burke Morrison, 2006; Henrich, Schwab-Stone, Fanti, Jones, & Ruchkin, 2004; Milam, Furr-Holden, & Leaf, 2010; Skiba, Simmons, Peterson, & Forde, 2006). In our assessment system, we use scales designed to measure the various aspects of social control noted above (i.e., Family Attitude toward Education, Family Involvement, Relationships with School Personnel), as well as measures of absenteeism and school mobility.

### Self-Regulation and Behavior

*Self-regulation* refers to the ability to self-manage or regulate attitudes, behaviors, and feelings that affect students' receptiveness to, and implementation of, learning activities (Robbins et al., 2009). Self-regulation is an important psychosocial domain reflected in the self-management and regulatory theories of Pintrich (1989, 2000a) as well as Schunk and Zimmerman (2003). The term self-regulation has been used in the educational psychology literature to capture the "active, constructive process by whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior" (Pintrich, 2000b, p. 453). From a dispositional perspective, we believe motivation is distinguishable (though not independent) from self-regulation. Thus, we believe that goal-setting and related behaviors tend to align more closely with motivation. Our definition of self-regulation emphasizes the cognitive (see Whiteside & Lynam's, 2001, Premeditation facet, which is defined as the tendency to think about the consequences of one's behavior before engaging in the behavior), behavioral (see Watson & Clark's, 1993, explication of behavioral disinhibition), and emotional aspects of self-regulation. Regarding the latter, emotion regulation is an important aspect of self-regulation, as it impacts a variety of self-regulatory processes (Cole, Martin, & Dennis, 2004; Gross, 1998). Thus, we believe that scales tapping these different aspects may be good markers of self-regulation. For example, a scale tapping the cognitive aspect measures whether students can control impulsive thoughts and actions. Similarly, a scale tapping the behavioral aspect assesses whether students are able to maintain appropriate behaviors and avoid disruptive behaviors. Finally, a scale tapping the emotional aspect captures how students experience and regulate emotions.

Using our expanded definition of the construct as a foundation, several studies have found a relationship between self-regulation and educational outcomes, including academic achievement and dropout (Fredricks, Blumenfeld, & Paris, 2004; Rumberger & Lim 2008). Some studies have even found a curvilinear relationship between self-regulation and GPA in that both the high and low ends of self-regulation scores were associated with lower first-year GPA in college (Robbins et al., 2006), whereas other studies have shown a linear relationship between self-regulation and academic achievement (Duckworth & Seligman, 2005; Wolfe & Johnson, 1995) in which higher levels of self-regulation are associated with higher GPA. In our assessment system, we use scales designed to measure all of

these aspects of self-regulation (i.e., Thinking before Acting, Orderly Conduct, and Managing Feelings).

### The Interplay of Academic Achievement and PSFs on Student Success

Previous research has shown that both standardized achievement and GPA are associated with measures of motivation and self-regulation in various age groups, and persistence is associated with measures of social control in college students (ACT, 2011; Robbins et al., 2006, 2004). A review of this literature (ACT, 2011) provided the following estimates for middle-school students.

- Motivation, as reflected in study habits and homework compliance, correlates .52 with prior grades and .27 with standardized achievement scores.
- Self-regulation, as measured by orderly conduct, also has a relatively high association with GPA ( $r = .37$ ) and standardized achievement ( $r = .28$ ), respectively.
- Social control, as measured by students' perceptions of family attitudes toward education, has a moderate association with GPA ( $r = .27$ ) and standardized achievement ( $r = .22$ ), respectively.

### Should We Expect School-Level Effects?

In a middle-school population, we found little evidence that students' PSFs vary considerably across school characteristics. Correlations between PSFs and middle-school characteristics were generally small: the percentage of minority students in a school (range = .00–1.14), the percentage of free- or reduced lunch recipients (range = 1.03–1.13), and average class size (range = .00–.13) (ACT, 2011). These findings are consistent with the literature showing that psychosocial and personality measures are generally unrelated to these types of school factors (Glovinsky-Fahsholtz, 1992; Wyss, Tai, & Sadler, 2007). Moreover, once students' pre-high school academic achievement is accounted for, high school characteristics have little relationship to later academic achievement, as measured by standardized test scores (Allen, Bassiri, & Noble, 2009). Because high school grades and academic failure may be affected by middle-school contextual factors, it is prudent to consider middle-school characteristics when modeling outcomes. Moreover, retaining the middle-school characteristics in our analyses of high school outcomes allows us to control for the context in which the PSFs and behavioral indicators were measured and to obtain an estimate of their relative importance.

### Testing our Assessment System

We were interested in three primary questions: First, what are the effects of different facets of academic preparation, PSFs (i.e., motivation, social control, and self-regulation), behavioral, school-level, and demographic factors when predicting high school academic performance, as measured by GPA? We hypothesized that prior academic performance (in middle school) and standardized achievement scores would be the strongest predictors of high school academic performance but that certain PSF and behavior facets would provide incremental prediction of such performance. Furthermore, we were interested in the effects of middle-school characteristics on student performance. There is some research (cf.

Rumberger & Lim, 2008) on the degree to which social control, such as aggregated student perceptions of safety and positive relationships, impact academic performance; it is less clear whether other school indicators (e.g., class size, aggregates of student poverty, proportion of minority students) are predictive of academic performance. In this respect, we hypothesized that school characteristics such as class size would have a small (but perhaps significant) role.

Second, we were interested in whether our assessment system could accurately identify students who are at risk for high school failure. In particular, how well does our system of measurements predict which students went on to obtain poor grades? We hypothesized that our full assessment system containing PSFs and behaviors would outperform models containing only prior academic performance and standardized achievement.

Finally, we were interested in the importance of PSFs and behaviors (considered as *sets* of predictor variables) for predicting academic performance, relative to that of traditional predictors (academic achievement and demographics). We hypothesized that PSFs and behaviors would explain a substantial amount of variance in academic performance.

## Method

### Sample and Procedure

A total of 4,660 middle-school students enrolled in seventh and eighth grade at 24 middle schools from 13 districts throughout the Midwest and the South participated in the study. These middle schools were selected because they (a) have a broad range of demographic and achievement characteristics and (b) use ACT's EXPLORE academic achievement test. Participating students mostly spoke English as their primary language (98%) and were Caucasian (62%).<sup>2</sup> Students' mean age was 13.5 years ( $SD = .7$ ), and the sample was evenly split on gender (51% male). Participating schools were given group summaries of their students' assessment results as an incentive for participating. A newly published assessment, ENGAGE Grades 6–9 (ACT, 2011), was administered to these students in a group setting during class time. Students were told that participation was voluntary, that they could terminate participation at any time without penalty, and that the questionnaire would require approximately 30 min of their time.

Of the initial sample of 4,660 students, 3,757 (81%) also took the EXPLORE assessment, which is typically administered in the eighth grade. Among students who took EXPLORE, 51% were male, 98% spoke English as their primary language, and 64% were Caucasian. Students varied in age from 12 to 16 years old ( $M = 13.6$ ,  $SD = .6$ ). Thus, the subsample of students who took EXPLORE was similar in demographics to the larger study sample.

As a condition for participating in the study, school districts agreed to provide follow-up information (i.e., enrollment status and high school grades) for the study sample. Follow-up information was obtained 2 years later for 3,325 students (enrolled in ninth and 10th grade at the time of follow-up), comprising 71% of the original study sample and 89% of the EXPLORE-tested sample. Demographic characteristics for the subsample of students with follow-up information were similar to those of the original sample (69% Caucasian; 51% male; 99% spoke English as primary language; mean age = 13.6,  $SD = .6$ ).

### Predictor Variables

This section describes the predictor variables that were used in developing regression models to test the incremental predictive validity of PSF scale scores and behavioral data obtained from ENGAGE. The predictor variables were considered in five sequential blocks: (a) school-level variables (e.g., % free lunch), (b) demographic factors (e.g., gender), (c) academic factors (e.g., prior grades), (d) behavioral factors (e.g., number of days absent), and (e) psychosocial factors (e.g., ENGAGE scales).

**Prior academic achievement.** Although grading standards may vary across middle schools, middle-school grades are strongly predictive of high school grades (e.g., Byrnes & Miller, 2007). Standardized achievement test scores have also been used in the past as traditional predictors of high school academic performance and persistence (e.g., Grigorenko et al., 2009). EXPLORE, designed to assess eighth- and ninth-grade students' academic achievement within four subject areas (English, mathematics, science, and reading), is annually administered to nearly 1 million students in the United States. It functions as the entry point of ACT's integrated curriculum-based assessment, Educational Planning and Assessment System (EPAS), with two other tests (PLAN and ACT) typically administered in 10th and 11th or 12th grade. The EXPLORE Composite score, ranging from 1 to 25, is the mean of the four subject area scores and has demonstrated high internal reliability ( $KR-20 = .94$ ) (ACT, 2007). Past studies show EXPLORE Composite scores are highly correlated with high school academic achievement, as measured by high school GPA ( $r = .55$ ; ACT, 2007; Woodruff, 2003). Because of the Composite score's established validity for predicting high school GPA, its high reliability (higher than the subject area scores), and its content area alignment to middle-school and early high school courses, it was used as the measure of prior academic achievement.

**Motivational, social control, and self-regulatory factors.** Parallel to the motivational, social, and self-regulatory mechanisms discussed earlier, part of the framework of this study is based on the psychosocial scales of ENGAGE (ACT, 2011). ENGAGE for Grades 6–9 was developed using a rational-empirical approach (Clark & Watson, 1995; Loevinger, 1957; Nunnally & Bernstein, 1994), with an emphasis on conceiving and measuring markers of the three broad psychosocial domains (cf. Le et al., 2005; Robbins et al., 2006, 2004, 2009). The instrument contains 106 items scored using a 6-point Likert-type scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The 10 ENGAGE scales range from nine to 12 items and have demonstrated moderate to high internal consistency reliabilities ( $\alpha$  range = .81–.90;  $Mdn = .87$ ), as well as modest incremental validity over demographic, school, and standardized achievement variables (ACT, 2011; Casillas et al., 2011). In confirmatory factor analyses, the scales fit a three-factor higher order structure consistent with the constructs of motivation, social control, and self-regulation (Casillas et al., 2011). These findings are consistent with the structure of a similar measure designed to assess PSFs in college students (see Le et al., 2005). Although the 10 ENGAGE scales can be grouped

<sup>2</sup> The remaining race/ethnicity breakdown was 16% Hispanic/Latino, 10% African American, 3% multiracial, 2% Asian American/Pacific Islander, 1% American Indian/Alaskan Native, and 7% "other" race/ethnicity or preferred not to respond.

to represent three broad domains, previous research suggests that the facet-level measurement of PSF characteristics have greater utility and are more likely to predict academic performance (cf. Lounsbury et al., 2003; Paunonen & Ashton, 2001). The 10 ENGAGE scales and their definitions with sample items are presented in Table 2; the table is organized by the three domains of motivation, social control, and self-regulation.

**Behavioral indicators.** Several behavioral indicators of the PSFs were identified, including absenteeism, being held back, time spent doing homework, and media time, as important variables likely to be predictive of student success (e.g., Gentile, Lynch, Linder, & Walsh, 2004; Kaufman & Bradbury, 1992; Rumberger, 1995; Rumberger & Larson, 1998). These items were included in the ENGAGE demographic section, and students were asked to rate the frequency or number of instances for each item. Definitions and sample items of the behavioral indicators also are presented in Table 2, below the psychosocial domains.

### Descriptive Statistics of the Predictor Measures

Descriptive statistics for study variables are organized by category and presented in Table 3. Means and standard deviations for study variables, particularly EXPLORE and ENGAGE, were consistent with prior samples using those measures (ACT, 2007, 2011). In addition, ENGAGE scales for the study sample showed good to excellent internal consistency reliabilities (Cronbach's  $\alpha$  range = .83–.92; *Mdn* = .88).<sup>3</sup>

### Outcome Variables

Because high school dropout often cannot occur before the age of 16 due to state mandatory school attendance requirements, we did not model actual dropout outcomes. Instead, early high school GPA (during either ninth or 10th grade) was used as a direct measure of academic performance. Failing one or more courses—and by extension, having a low high school GPA—can be considered a proxy of eventual dropout risk (see Mac Iver, 2010; Rumberger & Lim, 2008).

### Analyses

Multiple linear regression (MLR) was used to test our hypotheses that psychosocial and behavioral variables are predictive of high school GPA after controlling for traditional predictors (school-level, demographic, and academic achievement variables). Because of the nesting of students within schools, hierarchical linear modeling (HLM), where the regression coefficients could vary by school, was also considered. As detailed later in the Results, the parameter estimates from MLR were not tangibly different than the HLM-generated estimates. Furthermore, because the MLR model permits dominance analysis (description forthcoming), the MLR model was chosen over HLM.

**True positive and capture rates.** True positive and capture rates are measures of validity that are meaningful if a model's predicted values are used to identify students who are at high risk of failing academically in the future. Here, the true positive rate is defined as the probability of an unsuccessful outcome, given that a student is flagged for intervention. The capture rate is the probability of a student having been flagged, given that she or he

has an unsuccessful outcome. The true positive and capture rates are calculated as functions of  $R$  for linear regression models (Allen, Robbins, & Sawyer, 2010). Thus, the true positive and capture rates do not provide additional evidence on predictive validity (beyond that already provided by  $R$ ). However, the rates are a means of translating the purely statistical validity measure ( $R$ ) into one that is related to how the assessment system could be used in practice (see Messick, 1994, for discussion of consequences of assessment validity).

It was assumed that students ranking in the bottom  $p\%$  of predicted values ( $p = 5, 10, 25$ ) would be flagged, and true positive and capture rates for identifying students with early high school GPA less than 2.0 were calculated. Three models for identifying at-risk students were compared for each outcome: (a) random selection; (b) prior grades and EXPLORE Composite scores; and (c) prior grades, EXPLORE Composite scores, psychosocial variables, and behavioral indicators.

**Dominance analysis.** Because of correlation between and within sets of predictor variables, the relative importance of a set of predictor variables cannot be determined from regression coefficients. Accordingly, the dominance analysis technique (Azen & Budescu, 2003; Budescu, 1993) was used to compare the relative importance of each set of predictors. Dominance analysis is based on an examination of the  $R^2$  values for all possible *subset* models—or all possible models formed by each possible combination of predictor variables. The  $R^2$  attributed to each predictor is determined by analyzing the  $R^2$  values for all subset models to which the predictor belongs. The total amount of variation explained by each set of predictor variables is then obtained by summing the  $R^2$  attributed to each predictor within the set. For more technical details on how dominance analysis works, please see Budescu (1993) or Azen and Budescu (2003).

The dominance analysis technique is applicable to this study because the importance of each predictor is estimated irrespective of order of model entry. It is also conceptually appealing in that it makes no assumptions about the causal relationships between predictor variables in the model. For example, the dominance analysis technique allows us to measure the importance of academic achievement measures and psychosocial variables in predicting early high school GPA, without requiring us to specify a model for the relationship between the psychosocial and academic achievement variables. Such a model would likely need to capture complex relationships—such as the effects that motivation, social control, and self-regulation have on academic achievement and behavior indicators. Also important to the present study, dominance analysis allows us to estimate the importance of a *set* of predictors. Thus, the relative importance of prior grades, academic achievement, demographics, school characteristics, PSFs, and behavioral indicators are compared.

## Results

### Correlations With Early High School GPA

All academic, psychosocial, and behavioral indicators were significantly related (at the bivariate level) to early high school GPA

<sup>3</sup> A copy of the intercorrelation matrix of study variables is available from the authors upon request.

Table 2  
 ENGAGE Grades 6–9 Scale Definitions, Sample Items, and Behavioral Indicators

Domain	Scale name	Definition	Sample item
Motivation	Academic Discipline	Degree to which a student is hardworking and conscientious as evidenced by the amount of effort invested into completing schoolwork.	“I turn in my assignments on time.”
	Commitment to School	Commitment to stay in school and obtain a high school diploma.	“I am committed to graduating from high school.”
	Optimism	A hopeful outlook about the future in spite of difficulties or challenges.	“I am confident that everything will turn out all right.”
Social control	Family Attitude toward Education	Positive family attitude regarding the value of education.	“My family supports my efforts in school.”
	Family Involvement	Family involvement in a student’s school life and activities.	“I talk to my family about schoolwork.”
	Relationships with School Personnel	The extent to which students relate to school personnel as part of their connection to school.	“Adults at my school understand my point of view.”
	School Safety Climate	School qualities related to students’ perception of security at school.	“I feel safe at school.”
Self-regulation	Managing Feelings	Tendency to manage duration and intensity of negative feelings (e.g., anger, sadness, embarrassment) and to find appropriate ways to express feelings.	“I would walk away if someone wanted to fight me.”
	Orderly Conduct	Tendency to behave appropriately in class and avoid disciplinary action.	“I have been sent to the principal’s office for misbehaving.”
	Thinking before Acting	Tendency to think about the consequences of one’s actions before acting.	“I think about what might happen before I act.”
Behavioral indicators	Absenteeism	Number of absences, days tardy, and skipped classes reported by the student over the past month.	“How many days were you absent from school in the past month?”
	Held back	Having been held back from normal grade progress.	“Have you ever been held back from moving to the next grade?”
	Homework time	Time spent on homework on a typical school day.	“How many hours do you usually spend doing homework on a school day?”
	Media time	Time spent watching TV, playing video games, and surfing the Internet (for nonschool-related purposes) during a typical school day.	“How many hours do you usually watch TV on a school day?”
	School Mobility	Number of times that the student changed schools since starting elementary school.	“How many times have you ever changed schools?”

Note. From “ENGAGE Grades 6-9 User’s Guide, by ACT, 2011. Copyright 2011 by ACT. Adapted with permission.

(see Table 4). The bivariate associations of early high school GPA with middle-school grades ( $r = .64$ ) and EXPLORE Composite score ( $r = .56$ ) were the largest in magnitude. These were followed by the associations of the PSFs (range  $r = .18$ – $.48$ ;  $Mdn = .28$ ), the behavioral indicators (range  $r = 1.10$ – $1.41$ ;  $Mdn = 1.20$ ), demographic factors (range  $r = .05$ – $.29$ ;  $Mdn = .19$ ), and finally school-level factors (range  $r = 1.01$ – $1.21$ ;  $Mdn = 1.16$ ).

### Adequacy of MLR Model

Using MLR instead of HLM (Raudenbush & Bryk, 2002) permitted our use of the dominance analysis technique. However, because the nesting of students within schools calls for HLM, we conducted analyses to determine whether our results would have been different if HLM were used instead of MLR. We first fit a model with school-specific intercepts, also known as a *random*

*intercept model*. Although there was evidence of variation of intercepts across schools (variance estimate of  $.036$ ,  $p = .004$ ), the random intercept model results were very similar to the MLR results: The regression coefficient estimates for the student-level predictors (demographics, academic achievement, PSFs, and behavioral indicators) differed by 0.02 or less. All student-level predictors that were significant in the MLR were significant in the random intercept model, and vice versa. Next, we tested for random slopes—that is, whether there was significant variation in any of the predictor effects across schools. None of the slope variances were significant at the  $.05$  level, suggesting that the random intercept model was adequate and that the MLR results were not sensitive to model choice.

To examine whether the fitted model agreed with the assumptions of MLR, we examined the distribution of the model residuals. The distribution was bell-shaped and mostly symmetric, with a

Table 3  
Descriptive Statistics for Study Variables

Variable	<i>N</i>	<i>M</i>	<i>SD</i>
School level			
% free lunch	3,294	0.48	0.17
% minority	3,294	0.28	0.21
Average class size	3,294	227.26	79.56
Demographic			
Gender (male)	3,289	0.51	0.5
White	3,290	0.65	0.48
Black	3,290	0.09	0.29
Hispanic	3,290	0.15	0.36
Asian	3,290	0.02	0.12
Parent's education	2,596	4.05	2.04
Academic achievement			
Prior grades (5-point scale)	3,215	3.95	0.87
EXPLORE composite score	3,294	15.02	3.17
Behavioral indicators			
Number of days absent	3,276	0.72	0.99
Skipped class	3,282	0.15	0.46
Homework not done	3,274	1.27	0.89
Was held back	3,229	0.11	0.32
Media time (composite)	3,096	-0.01	0.7
Psychosocial			
Academic Discipline	3,284	4.83	0.89
Managing Feelings	3,283	3.87	1.17
Commitment to School	3,285	5.65	0.57
Family Attitude toward Education	3,283	5.57	0.63
Family Involvement	3,284	4.69	1.02
Optimism	3,284	4.82	0.92
Orderly Conduct	2,961	0.69	0.29
Relationships with School Personnel	2,420	3.98	1.02
School Safety Climate	3,281	4.21	0.94
Thinking before Acting	3,281	3.91	1.04

Note. Orderly Conduct is scored as yes/no; all other psychosocial scales are scored on a 6-point Likert scale.

slightly larger lower tail (skewness = -0.43). Examination of the variation of the residuals by levels of the linear predictor did not suggest heteroskedasticity (nonconstant variance of residuals).

### MLR Model Results

In Table 4, effect sizes are represented by beta weights (*b*) from the MLR model, interpreted as the estimated increase in GPA (in standard deviation units) associated with a standard deviation increase in the predictor, all other predictors being equal. Prior grades (*b* = .311) and EXPLORE Composite score (*b* = .297) were the strongest predictors, with significant incremental validity added by having homework done (*b* = -.102), Academic Discipline (*b* = .092), Orderly Conduct (*b* = .085), Family Attitude (*b* = .045), and number of days absent (*b* = -.039). Interestingly, the psychosocial variables Commitment to School (*b* = -.053) and Thinking before Acting (*b* = -.048) had negative weights in the MLR model. This is likely a product of multicollinearity and using a large number of predictor variables (26 total), as the bivariate correlations between Commitment to School and Thinking before Acting with early high school GPA were positive and significant. Overall, the MLR model had strong predictive strength of early high school GPA, with model *R* = 0.742.

Table 5 features accuracy of classification models based on true positive and capture rates. Both rates depend on the percentage of

students who are flagged: True positive rates decrease as the percentage of students flagged increase, whereas capture rates increase with an increase in the percentage of students flagged. The true positive and capture rates are functions of model *R*, the percentage of students flagged, and the overall percentage of students who fail (Allen, Robbins, & Sawyer, 2010). The needed model *R* values were obtained by fitting reduced forms of the MLR model presented in Table 4 (using only the variables specified as flagging variables in Table 5), the percentage of students flagged are assumed (5%, 10%, or 25%), and the overall percentage of students who fail is 29.6% based on the study data set. As shown in Table 5, use of prior grades and achievement score results in substantial increases in accuracy (i.e., increased true positive rate) over random selection for identifying students who subsequently earned a low GPA (i.e., < 2.0) during the ninth or 10th grades (probability increases over random selection by 0.577, 0.508, and 0.362 for 5%, 10%, and 25% of students flagged). Furthermore, the combination of prior grades, EXPLORE Composite score, and psychosocial and behavioral indicators results in the highest level of accuracy (a 0.609 probability increase over random selection, for a total accuracy of 0.905 when 5% of students are flagged). The capture rates also demonstrate the incremental utility of using psychosocial and behavior measures. When 25% of students are flagged, 55.5% of the students who will struggle academically in high school are included among those flagged based on prior grades and EXPLORE Composite scores. This percentage increases to 58% when psychosocial and behavioral indicators are also used for flagging.

Figure 1 reports the relative importance of each set of predictors in predicting early high school GPA using the dominance analysis technique (Azen & Budescu, 2003). One of the primary benefits of using the dominance analysis technique is that the relative importance of sets of predictors is measured, irrespective of sequence of entry into the model and irrespective of theorized directions of causality between predictors. The results in Figure 1 show that prior grades were the most important predictor, with 30% of the explained variation attributed to it. Next, came EXPLORE Composite (25%), PSFs (23%), behavioral indicators (10%), demographic variables (9%), and school characteristics (3%). The dominance analysis shows that PSFs are a key contributor when the sequence of model entry is ignored.

### Discussion and Future Research

This study expands our previous longitudinal research bridging high school and college (cf. Robbins et al., 2006), which modeled college academic performance and persistence with high school GPA, standardized achievement, PSFs, and demographics. In the present longitudinal study, we also included behavioral indicators and school-level factors to build a comprehensive assessment system for predicting high school academic performance. In this study, we examined the role played by middle-school students' previous academic achievement, PSFs, behavioral indicators, demographics, and school-level factors. We took a methodological-substantive approach (cf. Marsh & Hau, 2007) by evaluating our assessment system using the dominance analysis technique (Azen & Budescu, 2003; Budescu, 1993), which allowed us to compare the relative importance of each set of predictors in the assessment system. Consistent with our hypotheses, the findings confirm that

Table 4  
Correlations and Beta Weights for Predictors of Early High School Grade Point Average

Predictor	<i>r</i>	Multiple linear regression model			
		<i>b</i>	se( <i>b</i> )	<i>t</i>	<i>p</i>
School level					
% free lunch	-.16	0.018	0.022	0.82	.412
% minority*	-.21	-0.060	0.018	-3.32	.001
Average class size*	.01	-0.099	0.017	-5.74	<.001
Demographic					
Gender (male)*	-.17	-0.066	0.013	-5.21	<.001
Race/ethnicity					
White	.26	0.032	0.021	1.54	.124
Black	-.16	-0.027	0.016	-1.64	.101
Hispanic	-.17	-0.029	0.018	-1.57	.116
Asian	.05	0.020	0.013	1.57	.118
Parent's education*	.29	0.034	0.013	2.62	.009
Academic achievement					
Prior grades*	.64	0.311	0.016	19.05	<.001
EXPLORE composite score*	.56	0.297	0.015	19.98	<.001
Behavioral indicators					
Number of days absent*	-.22	-0.039	0.012	-3.15	.002
Skipped class	-.22	-0.021	0.013	-1.60	.109
Homework not done*	-.41	-0.102	0.015	-6.89	<.001
Was held back	-.20	-0.024	0.012	-1.95	.052
Media time	-.19	0.009	0.013	0.72	.474
Psychosocial					
Academic Discipline*	.48	0.092	0.020	4.57	<.001
Managing Feelings	.34	0.023	0.017	1.36	.174
Commitment to School*	.26	-0.053	0.016	-3.23	.001
Family Attitude toward Education*	.26	0.045	0.017	2.65	.008
Family Involvement	.28	0.024	0.017	1.37	.170
Optimism	.27	-0.011	0.017	-0.67	.506
Orderly Conduct*	.43	0.085	0.016	5.20	<.001
Relationships with School Personnel	.28	0.017	0.017	0.96	.335
School Safety Climate	.18	0.015	0.015	0.95	.340
Thinking before Acting*	.24	-0.048	0.016	-3.03	.003
Model <i>R</i>		0.742			

Note. *n* = 3,278 for multiple regression models. Correlations  $\geq$  |.05| are significant (*p*  $\leq$  .01).

\* *p*  $\leq$  .01, in the multiple linear regression model.

academic achievement indicators are among the strongest predictors of future academic success. This is consistent with the findings of earlier longitudinal studies in which students' prior course performance was a key indicator of high school performance and subsequent graduation (Bowers, 2010; Mac Iver, 2010).

Also consistent with our hypotheses, the findings confirm that PSFs and behavioral indicators contribute to the prediction of future academic performance and thus can be useful in identifying middle-school students who are at high risk of failing academically. This has significant implications for combining psychosocial and behavioral information with academic achievement information to support the timely identification of students who are academically at risk. As demonstrated in this study, the PSFs and behavioral factors in question were clearly present in middle school and can be assessed and used to help students to better prepare for—and successfully navigate—the transition from middle to high school.

With this enhanced level of combined achievement, psychosocial, and behavioral information, intervention programs can be more successfully directed toward the students who need help based on their individual profiles. Compared with early

warning systems based on archival data alone (e.g., Balfanz et al., 2007), our findings show that including psychosocial characteristics provides modest but significant incremental power for predicting later academic achievement. More important than the improvement in statistical prediction (in terms of *R*), measuring psychosocial characteristics can help educators understand why students are at risk. Indeed, as the dominance analysis shows, a substantial amount (33%) of the explained variation in early high school GPA was attributed to PSFs and behavioral indicators. Clearly, these factors play a prominent role in understanding students' risk for academic difficulties and may be key in developing timely and effective interventions for helping students to succeed academically.

Interestingly, the most predictive psychosocial and behavioral variables in the MLR model (see bivariate and standardized effects from Table 4) were homework not done, Academic Discipline, Orderly Conduct, and Family Attitude toward Education. These predictors span the range of the three theoretical domains measured by ENGAGE (i.e., motivation, self-regulation, and social control) confirming that each of these domains is important in understanding academic success (and risk) from a psychosocial perspective.

Table 5  
Accuracy of Identifying Students With Early High School Grade Point Average < 2.0

Flagging variable	True positive rate	Capture rate
5% flagged		
1. None (students flagged at random)	0.296	0.050
2. Prior grades, EXPLORE composite	0.873	0.147
3. Prior grades, EXPLORE composite, psychosocial variables, & behavioral indicators	0.905	0.153
10% flagged		
1. None (students flagged at random)	0.296	0.100
2. Prior grades, EXPLORE composite	0.804	0.271
3. Prior grades, EXPLORE composite, psychosocial variables, & behavioral indicators	0.839	0.283
25% flagged		
1. None (students flagged at random)	0.296	0.250
2. Prior grades, EXPLORE composite	0.658	0.555
3. Prior grades, EXPLORE composite, psychosocial variables, & behavioral indicators	0.687	0.580

*Note.* The true positive rate is the probability of having early high school grade point average (GPA) < 2.0 among students scoring in the bottom  $p\%$  on the flagging variables ( $p = 5, 10, 25$ ). The capture rate is the probability of scoring in the bottom  $p\%$  on the flagging variables among students with high school GPA < 2.0.

These findings also are consistent with previous research linking these same three characteristics to academic performance. For example, several studies (e.g., Lounsbury et al., 2003; Peterson, Casillas, & Robbins, 2006; Robbins et al., 2006) have found that students who consistently invest effort in their schoolwork (i.e., those who score high on measures of academic discipline) earn higher grades and are more likely to persist into subsequent years of schooling. Similarly, the literature supports that students who demonstrate appropriate class behaviors and follow classroom and school rules (i.e., those who score high on measures of conduct or behavioral constraint) also tend to perform better academically (e.g., Kaufman & Bradbury, 1992; Watson & Clark, 1993). Furthermore, studies suggest that a supportive family attitude toward education plays a positive role in students' own attitudes regarding education as well as in their academic achievement (e.g., Cherian & Cherian, 1996; Maras, Carmichael, Patel, & Wills, 2007).

Contrary to our expectations, Thinking before Acting was negatively related to high school GPA in the full regression model, suggesting that higher levels of this facet of self-regulation may be detrimental, all else being equal. In a post hoc analysis, we examined whether this relationship was dependent on other self-regulation measures also being in the model. After removing the

other two self-regulation facets (Orderly Conduct and Managing Feelings) from the model, the negative effect of Thinking before Acting was no longer present. Recalling an earlier study in which both the high and low ends of self-regulation scores were associated with lower first-year GPA in college (Robbins et al., 2006), one explanation for the present findings is that Thinking before Acting (after controlling for Orderly Conduct and Managing Feelings) measures aspects of self-regulation that may be detrimental.

Overall, the findings from this study demonstrate the importance of including a comprehensive assessment system to evaluate the interplay of multiple factors (academic achievement, psychosocial, behavioral, demographic, school-based) in understanding academic performance. By measuring the range of factors related to academic success (or risk) in the present study, educators can align interventions to students' unique needs and have a better chance of improving their performance. Indeed, educators need to be able to address students' psychosocial needs before they manifest in failing grades or dropout. There is some research on the positive effects of self-regulatory, motivational, and social skills training on students (e.g., Pintrich & DeGroot, 1990) and on workers (e.g., Lord, Diefendorff, Schmidt, & Hall, 2010). More research is needed to better map interventions onto students' psychosocial needs and to understand how institutional and family contexts can either facilitate or impede the effectiveness of interventions.

From an individual student narrative perspective (cf. McAdams & Olson, 2010), understanding the unique interplay of school, family, and individual academic and nonacademic factors allows schools to better know each student, be able to tell that student's "story," and use the aforementioned factors to make more informed decisions (e.g., Balfanz et al., 2007). For example, in our interactions with school administrators, we have found that those students who are at moderate risk but who are not acting out (and thus not drawing as much attention to themselves) are often missed by school personnel trying to identify students who need additional support or interventions. These students actually may be among

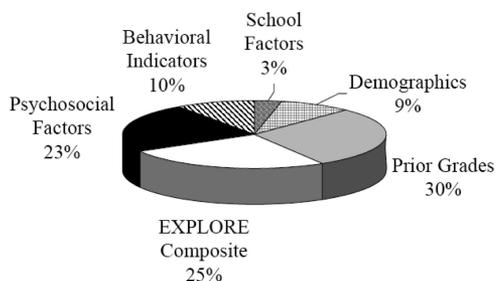


Figure 1. Relative strength of predictors of early high school grade point average.

the most responsive to intervention and prevention strategies. Thus, we see the use of a broad measure of PSFs and behavioral indicators as key to helping tell each student's "story" and to tailoring interventions in order to increase a student's chance of success, whether in core academic areas (e.g., math, English) or in the behaviors and attitudes that support academic performance (e.g., positive attitudes toward education, prosocial behavior, increased engagement).

At the institutional level, some of the ways that measures of PSFs and behavioral indicators can be used include (a) use in student-level data dashboards and other early warning systems to identify at-risk students and (b) looking at aggregate data (at the classroom, school, or district level) to monitor student characteristics and plan system-wide interventions and resources. At the family level, measures of PSFs can be used to (a) provide parents/guardians with information that can facilitate conversations and engagement regarding their students' academic lives and (b) help them monitor whether their students are developing the characteristics needed for academic success. Understanding student risk and student persistence over time is essential if we are to reduce the shockingly high dropout rates and low achievement rates in our K–12 educational system (cf. Balfanz et al., 2007; Rumberger & Lim, 2008).

The present study has a number of strengths and weaknesses. In terms of strengths, we studied a large cohort of students across 24 middle schools and 13 districts throughout the Midwest and Southern regions of the United States from seventh and eighth grade through early high school. We maintained a fairly high follow-up rate (71% of the original sample). Furthermore, we included a broad range of psychosocial and behavioral predictors of academic performance based on motivational, social control, and self-regulatory theories. Our set of predictors also included a broad range of more "traditional" variables, such as prior grades, standardized achievement test scores, demographics, and school-level factors. Altogether, our assessment system is among the more comprehensive available in the literature.

In terms of weaknesses, the sample was not fully demographically representative, particularly in terms of geographic location and the type of community in which the schools are embedded (e.g., urban, suburban, rural). Also, the behavioral and psychosocial data we used were based on student self-report, which may have weakened our findings if students did not provide accurate information (e.g., conduct problems, being held back, number of school moves). Thus, future research should obtain more objective behavioral data, whether via institutional records or teacher and counselor ratings of corresponding motivational, social control, and self-regulatory behaviors.

Our findings suggest that specific measures of motivational, social control, and self-regulatory factors are related to subsequent academic performance and course failure, which is a precursor to dropout. We recognize that the distinction between PSFs and behaviors (which typically are reported by other observers as opposed to the students themselves) is not clearly delineated in this study and that both of these are related to the expected outcomes. Future research would benefit from further clarifying the distinction between PSFs and behaviors and the role each plays in predicting academic outcomes. Our focus was on developing a comprehensive assessment system to improve prediction of aca-

demic risk and to better understand the combined contribution of PSFs and past behavior.

We did not investigate the moderating effects of PSFs and school-level factors across time, which constrains our understanding of how individual and school-level effects may interact to affect outcomes. Future research should further explore the differential effects of PSFs by academic achievement level. As Judge, Klinger, and Simon (2010) recently demonstrated, higher able individuals have higher growth (relative to others) in two important indicators of career success (income and occupational prestige) over time. That is, higher able students appear to benefit from human capital or external resources in ways lower able students do not. It may be that PSFs moderate achievement growth at higher rates for higher able students than for lower able ones. An interaction between achievement level and PSFs would have significant policy implications as we observe increasing disparity between high- and low-able students across time (Gordon & Dew-Becker, 2007; Konstantopoulos, 2008). As Judge et al. (2010) point out, interventions must be designed in ways that assist disadvantaged students even though, paradoxically, they may help advantaged students even more (see Ceci & Papierno, 2005, for a discussion).

In terms of more theoretical issues, our line of research now spans middle school to college and focus on a core set of psychosocial domains (i.e., motivation, social control, and self-regulation) that have demonstrated relevance across several developmental stages and may be considered common factors. Future research should explore how these factors manifest across development (particularly in the transitions from one educational stage to another as well as from school to work) and whether these same factors predict the broader range of outcomes relevant to the world of work. For example, based on existing research, we expect that motivational factors remain important regardless of age and setting (e.g., Joseph & Newman, 2010; Lord et al., 2010); however, we may find that others are more salient for a particular age group (e.g., the role of orderly conduct in young adolescents).

We took a facet rather than a domain measurement approach because we believe facets are more proximal to observable and malleable behavior, and are valid predictors of educational and work success (e.g., Lounsbury et al., 2003; Paunonen & Ashton, 2001; Peterson et al., 2006). One drawback to this approach is that our statistical model for early high school GPA used many individual predictor variables (26), which increases the probability of significant findings that are simply due to chance. Related to this issue, we observed two regression coefficients in our regression model that were statistically significant, but in an unexpected negative direction. Future research should explore the relative predictive effects of PSFs along different levels of a hierarchy (ranging from behaviors to broad domains) to better understand developmental differences and key moderators of educational achievement, persistence, and academic risk.

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