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Additive or Multiplicative? Predicting Academic Outcomes from Self-Regulation and Context

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Abstract

Many studies have documented the role of self-regulation in predicting academic outcomes. However, fewer have comprehensively measured self-regulation or considered it simultaneously with contextual variables to test formally the often-advanced "risk-buffering" hypothesis, wherein self-regulatory skill protects against contextual risk factors. In a large, regionally representative sample of U.S. adolescents, we linked self-reported demographics, self-regulation, and academic outcomes to Census data assessing neighborhood context and administrative data measuring economic disadvantage and achievement levels on state end-of-grade tests. We find inconsistent evidence for a risk-buffering role of self-regulation in the prediction of academic outcomes. Rather, we demonstrate that self-regulation is independently associated with academic outcomes, even when controlling for demographics and context.

Keywords

Self-regulation; academic performance; adolescence; context

The strategies and skills by which individuals manage their emotions, thoughts, and behaviors in the service of goal pursuit—termed *self-regulation*—are foundational underpinnings of achievement, facilitating skills necessary for academic outcomes (Blair & Raver, 2015). The ability to regulate cognitions, emotions, and behaviors; to inhibit impulses and initiate goal-consistent behavior; and to persist despite setbacks are consistently linked with academic outcomes including grades and standardized test scores (Robson et al., 2020), as well as downstream consequences like educational attainment (Moffitt et al., 2011). Self-regulation enables students to plan their goal pursuit, maintain attention while problem-solving, sustain motivation when faced with setbacks, and resist temptations (Panadero, 2017). Self-regulation should be pivotal for academic outcomes during adolescence, when

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self-regulatory demands increase as autonomy, course difficulty, and school structure change substantially (Eccles & Roeser, 2011).

Although self-regulation is linked with academic outcomes, these outcomes are multiply determined. Beyond personality factors like self-regulation, contextual factors characterizing students' families, homes, and neighborhoods are associated with academic outcomes. Proximal contexts such as the family and home environment and more distal contexts like neighborhoods predict academic outcomes from early childhood to adolescence and beyond (Leventhal & Brooks-Gunn, 2000). Experiences of childhood adversity attributable to context are associated with poorer academic outcomes across studies (Sirin, 2005). Children experiencing economic disadvantage and living in chaotic households, on average, demonstrate less academic achievement and educational attainment relative to more privileged counterparts (Garrett-Peters et al., 2016; Heckman, 2006).

Prior research suggests three possible models predicting academic outcomes from self-regulation and contextual factors. First, self-regulation and contextual factors could serve as independent predictors, positioning self-regulatory skills and contextual factors as relevant for academic outcomes, with neither qualifying nor accounting for the effects of the other. Several studies demonstrate self-regulation independently predicts academic outcomes, even when controlling for demographics and context (Howard & Williams, 2018) and IQ (Wu et al., 2017). However, others show that self-regulation lacks predictive utility when considered simultaneously with context (Pearce et al., 2016).

An alternative model posits an interaction between self-regulation and context on academic outcomes. Here we might observe a *risk-buffering* pattern wherein advantageous traits and skills—like self-regulation—can overcome some of the undesirable outcomes associated with adversity. In this model, self-regulation serves as a moderator; a psychological resource that becomes increasingly valuable as contexts become less favorable. For adolescents situated in goal-supportive contexts, self-regulation may be less necessary for academic outcomes, which are readily endorsed by peers, family, or neighborhood. Though self-regulation seems crucial in the presence of contextual risk factors for externalizing problems like substance use (Wills et al., 2001), its role when contextual factors do not favor academic achievement is murkier. Some studies find that self-regulation buffers against contextual risk factors (Razza et al., 2010; Wang et al., 2017); others show self-regulation is universally beneficial for academic outcomes (McClelland & Wanless, 2012), supporting the additive model.

Finally, self-regulation could mediate the relationship between contextual factors and academic outcomes (Evans & Rosenbaum, 2008). Though we cannot rigorously model mediated effects using cross-sectional data (Pek & Hoyle, 2016), we can test whether self-regulation and contextual factors are related—a necessary, though insufficient, condition for mediation. Though we test these correlations, we focused our predictive models on the additive effects of self-regulation and contextual factors on academic outcomes and potential interactions between self-regulation and contextual factors.

One complication in modeling these associations is that self-regulation research is plagued by measurement issues (cf. Duckworth & Kern, 2011). Self-regulation is often conceptualized and measured narrowly; many studies consider only specific features of self-regulation such as low impulsivity (e.g., Lozano et al., 2014). Though no overarching model of self-regulation exists (cf. Nigg, 2017), we operationalize self-regulation broadly by drawing on developmental and social-psychological conceptualizations, including multiple measures of self-regulatory skills relevant for academic outcomes.

In the present study, we examine how self-regulation and contextual factors are additively and interactively associated with academic outcomes. We build on existing work by examining these outcomes in a large, regionally representative sample of adolescents in the U.S., with comprehensive measurement of self-regulation and multiple indicators of academic success. Given limited prior support for an interactive effect of self-regulation and contextual factors, we did not expect to see strong evidence of interactions on academic outcomes. However, given our broad conceptualization and previous work showing unconditional effects of self-regulation, we hypothesized that self-regulation would predict academic outcomes, even when accounting for contextual factors that should affect adolescents' academic achievement.

Method

Participants

Participants were sampled from the public-school student population in North Carolina, a state in the Southeastern U.S., using administrative data from the North Carolina Department of Public Instruction (N = 2,104; see Table S1 for demographics; Figure S1 for locations within state). For reported analyses, we restricted the sample to participants with data available on at least one of three administrative variables: economic disadvantage, reading achievement level, and mathematics achievement level. The analysis sample was adequately-sized to ensure statistical power[1], representative of the population of North Carolina public-school students concerning sex and ethnicity, and slightly less economically disadvantaged (N = 1,982; M_{age} = 12.35, SD = 1.11; see Table 1).

Procedure

After interviewers gained parental consent and adolescent assent, participants completed the 90-minute phone survey. Adolescents reported on demographics, home environment, self-regulation, physical and mental health, problem behaviors, academics, and technology use (see Supplement for details and full list of measures). Participants completed the survey privately and received breaks to avoid response fatigue. They received a $30 gift card or check for participation.

Measures

Self-regulation.—We measured self-regulation using five self-report measures. Scores were combined to produce a single composite (α = .87). These measures address self-

[1]Post-hoc power analysis shows our power to detect small effects (ΔR^2 = .01–.02) at p = .05 ranges from .97–1 across outcomes.

regulatory skills relevant for academic goal pursuit, rather than individual preferences for self-regulation (e.g., regulatory focus). We included multiple measures to capture the common thread across conceptualizations of self-regulation. *Self-control*—in-the-moment inhibition of goal-inconsistent responses and initiation of goal-consistent responses—was measured with the Capacity for Self-Control Scale (Hoyle & Davisson, 2016; α = .70). We assessed adolescents' tendency to exercise *self-regulation* with the Questionnaire on Self-Regulation (Novak & Clayton, 2001; α = .80), tapping *behavioral*, *cognitive*, and *emotion regulation*. *Effortful control*—temperamental tendencies to regulate actions, attention, and emotions (Eisenberg et al., 2011)—was measured with the Early Adolescent Temperament Questionnaire (Ellis & Rothbart, 2001; α = .77). We measured *grit*, the ability to persevere and maintain interest toward goals, using the Short Grit Scale (Duckworth & Quinn, 2009) (α = .66). We assessed *impulsive* behavioral tendencies with the UPPS-P Child Impulsive Behavior Scale (Zapolski et al., 2010; α = .84).

We evaluated whether the correlations between these measures (mean r = .58; range .41–.69) were attributable to a single latent factor using confirmatory factor analysis. Our single-factor measurement model fit the data well (see Supplement), therefore, we use the unit-weighted composite, which does not assume factor scores generalize across samples.

Demographics.—Adolescents reported their sex, race, ethnicity, and age. Race and ethnicity (Hispanic/Latino) were assessed separately, combined into the following categories, and dummy-coded for analyses: non-Hispanic White, non-Hispanic Black, non-Hispanic American Indian, non-Hispanic Asian, non-Hispanic Native Hawaiian/Pacific Islander, multiracial, and Hispanic only (missing race).

Contextual factors.—We measured family, home, and neighborhood context using self-reports, administrative data from school records, and Census data. Adolescents answered a single item regarding *subjective socioeconomic status* (SES), "In your opinion, how is your family doing financially?" (response scale: 0, *we do not have enough money to meet basic needs*, to 3, *we have enough money to do most anything we want*). Family *economic disadvantage* was based on eligibility to receive free and/or reduced lunch, using administrative data. Adolescents' perceptions of the home context were assessed using a 6-item measure of *household chaos* (Matheny et al., 1995; α = .64). Neighborhood context was assessed using two variables geocoded from American Community Survey 5-year estimates for 2010–2014. We quantified *neighborhood income inequality* using the tract-level Gini coefficient, an index of income inequality (Deininger & Squire, 1996) where higher proportions (scale: 0–1) indicate more inequality. *Neighborhood educational attainment* was the proportion of adults over 25 in the Census block group with a bachelor's degree or higher.

Academic performance and aspirations.—We assessed academic performance using multiple indicators from self-reports and administrative data. Adolescents self-reported past-year grades using a 10-point scale ranging from 1, *mostly Fs* to 10, *all As*. We obtained achievement levels on state end-of-grade tests in reading and mathematics from administrative data. These achievement levels indicate subject material command ranging from 1, *limited command*, to 5, *superior command*. Students scoring at level 3 and above are

considered proficient at grade level, whereas levels 4 and above meet college- and career-readiness standards. As in other research demonstrating their validity (Sticca et al., 2017), in our sample, self-reported grades correlated significantly with math (r = .50) and reading (r = .55) achievement levels (see Table S3).[2] Finally, we measured educational aspirations by asking how much school adolescents hoped to complete (scale: 1, *some high school*, to 6, *graduate school*).

Analytic strategy.—We estimated hierarchical multiple regression models in SAS 9.4. We first added age and sex to the model, and then entered dummy-coded race/ethnicity variables simultaneously to examine the change associated with the demographics. Next, we added the set of contextual variables (subjective SES, economic disadvantage, Gini coefficient, neighborhood educational attainment, and household chaos) to the model. We then entered the self-regulation factor to examine whether it predicted academic outcomes over and above demographics and the contextual variables. Finally, we individually examined interactions between self-regulation and contextual variables to test whether self-regulation moderates their effect on academic outcomes. We used a two-tailed minimum cutoff value of $p < .01$ and refer to parameter tests yielding a p-value of .01 or less as significant. Results are organized by the criterion variables tested in our analyses.

Results

Correlations between self-regulation and context.

First, we examined correlations between our self-regulation composite and the set of contextual variables (see Table S3). Of the contextual variables, only household chaos was strongly correlated with self-regulation, $r = -.35$, with adolescents living in more chaotic households scoring lower on self-regulation.

Self-reported grades.

Next, we tested whether context and self-regulation predict unique variance in adolescents' self-reported grades beyond demographics. Of the contextual variables, only neighborhood income inequality failed to predict grades. When we added self-regulation to the model, it predicted significant additional variance, corresponding to a small-to-medium-size effect ($\Delta R^2 = .078$) of self-regulation on grades (see Table 2). The unstandardized regression weight suggests that for every unit increase in self-regulation, we should see a parallel increase of nearly a full letter grade. Finally, we observed a significant interaction between neighborhood educational attainment and self-regulation. Simple slope analyses at high (+1 *SD*) and low levels (−1 *SD*) of self-regulation showed that neighborhood educational attainment was more strongly related to self-reported grades for adolescents low in self-regulation ($B = 1.43$, $p < .0001$) than their high self-regulation counterparts ($B = 0.35$, $p = .06$) (see Figure 1), and did not predict grades for students one standard deviation or more above the mean on self-regulation.

[2]In a subsample with available parent data ($N = 222$), adolescents' self-reported grades correlated well with parents' reports on the same item, $r = .74$, $p < .0001$.

Educational aspirations.

Next, we examined the impact of demographics, context, and self-regulation on educational aspirations. Adolescents who were less economically disadvantaged, living in less chaotic households, and living in neighborhoods with more educational attainment hoped to complete more education. Self-regulation explained a small but significant amount of additional variance ($\Delta R^2 = .012$). Adolescents high in self-regulation hoped to complete more schooling (see Table 3).

Self-regulation also moderated the relationship between economic disadvantage and educational aspirations. Simple slope analyses conducted at high (+1 *SD*) and low levels (−1 *SD*) of self-regulation showed a strong association between economic disadvantage and educational aspirations for adolescents low in self-regulation ($B = 0.31$, $p < .0001$), but no effect for high self-regulators ($B = 0.04$, $p = .60$) (see Figure 2). However, consistent with other research (e.g., Beal & Crockett, 2010), the sample mean indicated most already aspired to complete a four-year degree.

Math and reading achievement levels.

Math achievement levels.—Among the contextual variables, only local income inequality failed to predict math achievement levels.[3] When we added self-regulation to the model, it predicted a small, but significant, amount of additional variance in math achievement, corresponding to a small-to-medium size effect ($\Delta R^2 = .029$). Although self-regulation and selected contextual factors were individually related to math achievement, self-regulation did not function as a moderator (see Table 4).

Reading achievement levels.—All contextual variables predicted reading achievement, with less economic disadvantage, less neighborhood income inequality, less household chaos, higher rates of neighborhood educational attainment, and higher subjective SES associated with higher reading achievement levels (see Table 5). Self-regulation again explained a small but significant amount of additional variance, corresponding to a small effect ($\Delta R^2 = .016$) on reading achievement. For each unit increase in self-regulation, there is a parallel nearly half-unit increase in achievement levels, which could mean the difference between meeting and failing to meet on-grade-level standards.

As with grades, we observed a significant interaction between neighborhood educational attainment and self-regulation (see Figure 3). Slopes were non-zero for low ($B = 1.70$, $p < .0001$) and high self-regulation ($B = 1.06$, $p < .0001$) adolescents. Although the effect is stronger for students lower in self-regulation, neighborhood educational attainment is associated with reading achievement across the range of self-regulation.

Discussion

In a representative sample of adolescents, we examined the additive and interactive effects of self-regulation and contextual risk factors on academic performance. Self-regulation was

[3]We replicated this pattern—whereby neighborhood income inequality inconsistently predicted academic outcomes—using median neighborhood household income estimates.

associated with multiple indicators of academic success including achievement levels on state end-of-grade tests, self-reported grades, and educational aspirations. Effect sizes for self-regulation controlling for demographics and contextual factors were in the small-to-medium range, consistently adding to the prediction of multiply determined academic outcomes. We find only inconsistent evidence—for self-reported grades and, to a lesser degree, educational aspirations and reading achievement—that self-regulation is differentially important as a function of contextual factors. Taken together, these findings underscore the relevance of self-regulatory skills for academic outcomes across levels of relative advantage, regardless of whether environments support academic goal pursuit.

These findings add to the growing literature (Wu et al., 2017) linking self-regulation with academic outcomes, even in the presence of contextual factors commonly associated with achievement. As in prior research, we found only inconsistent evidence of interactions between self-regulation and contextual factors. Rather, our results emphasize that self-regulation is beneficial for academic outcomes across a range of diverse contexts. We replicate existing work connecting contextual factors and academic outcomes (Sirin, 2005) and, yet, we find that the effects of contextual factors and self-regulation are primarily additive. Moreover, in a sample including the full range of self-regulatory skills, we do not find that adolescents experiencing adversity are simply low in self-regulation. Contextual variables and self-regulation were generally uncorrelated, suggesting that contextual effects are likely not mediated by self-regulation. In additive models accounting for context, self-regulation predicts academic outcomes, though observed effect sizes were generally in the small-to-medium range.

Our results echo existing work showing the importance of self-regulation for academic outcomes, highlighting that the strategies afforded by skillful self-regulation promote academic goal pursuit. By operationalizing self-regulation as a latent variable encompassing multiple facets of the construct, we add to a literature that often measures only a single facet of the construct. Our findings suggest that the underlying trait reflected in a constellation of self-regulatory strategies and skills—from emotion regulation to self-control and grit—facilitates academic success. We echo other calls for thorough measurement (Eisenberg et al., 2019) to model more precisely relationships between self-regulation and academic outcomes.

Though our study includes a regionally representative sample and thorough assessment of self-regulation, it still has limitations. Our measure of school performance was past-year self-reported grades. Due to the age of our sample, objective indicators of overall performance (e.g., GPA) were unavailable in administrative records. However, we replicate other work (Sticca et al., 2017) showing that self-reports correlate well with achievement levels on state end-of-grade tests, suggesting that self-reports in terms familiar to students (e.g., “mostly As”) may be a suitable proxy for more objective measures of academic performance. Additionally, our cross-sectional data prevents us from addressing causality or testing for mediation. Nevertheless, our correlational findings underscore the importance of self-regulation for academic outcomes across contexts.

Our findings echo extant research establishing independent associations between self-regulation and academic outcomes (Duckworth et al., 2019) and indicate that person-level factors like self-regulation could be strengthened to improve academic outcomes regardless of context. Despite growing evidence that self-regulation predicts academic outcomes even when controlling for contextual factors and intelligence (e.g., Wu et al., 2017), few interventions target self-regulatory processes directly (but see, Schmitt et al., 2015). Although context-specific interventions would likely be most promising, our findings that the relationship between self-regulation and academic outcomes is not conditional on context suggest that interventions to bolster self-regulatory skills (e.g., Duckworth et al., 2013) should have modest but positive effects on academic outcomes regardless of individual risk factors stemming from suboptimal contexts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- We combined survey, administrative, and Census data in a representative sample of adolescents.
- We tested independent and joint effects of context and self-regulation on academics.
- Our comprehensive self-regulation measure was uniquely associated with academic outcomes.
- Higher self-regulation was associated with better academic outcomes across context.
- The self-regulation effect was consistent, even when controlling for demographics and context.

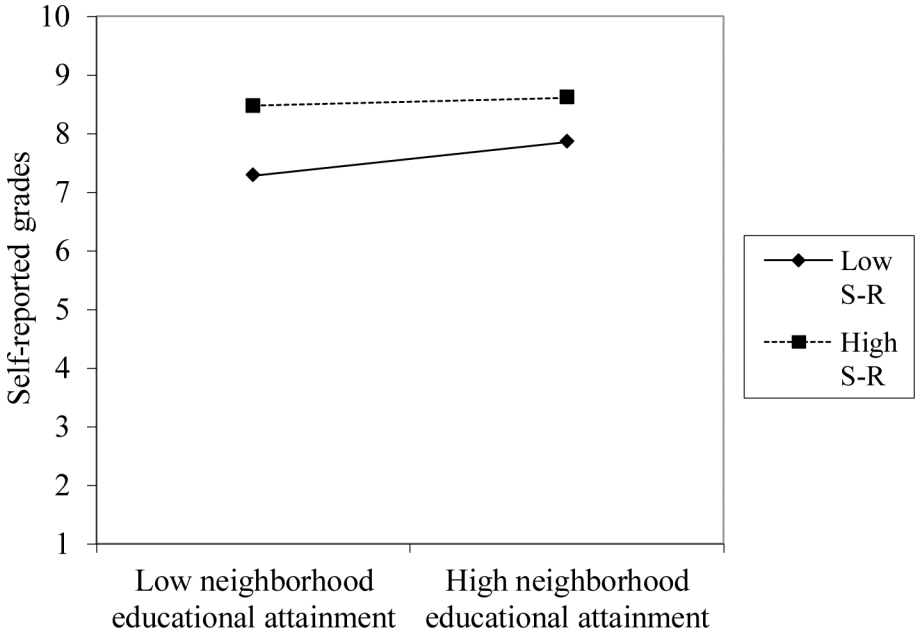

Figure 1.

Self-reported grades as a function of neighborhood educational attainment (low: −1 *SD*, high: +1 *SD*) and self-regulation (low: −1 *SD*, high: +1 *SD*). Only low self-regulation slope is significant.

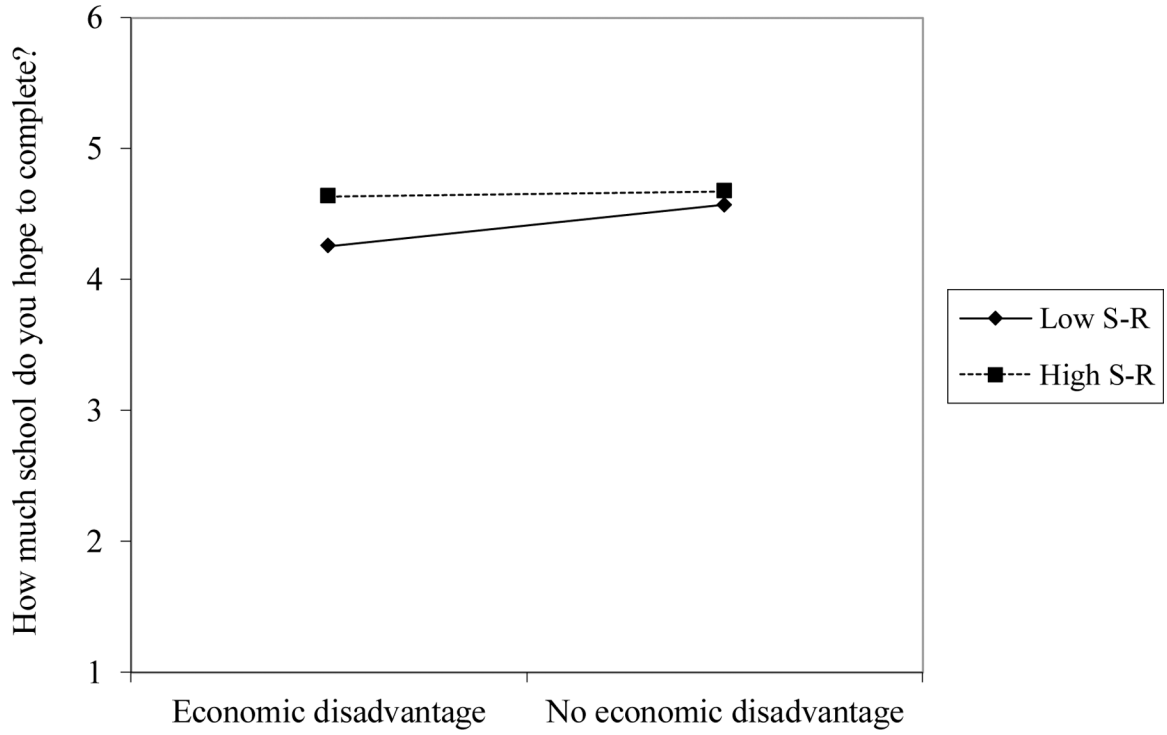

Figure 2.

Educational aspirations (*scale*: 1 = *some high school*, 6 = *graduate school*) as a function of economic disadvantage and self-regulation (low: −1 *SD*, high: +1 *SD*). Only low self-regulation slope is significant.

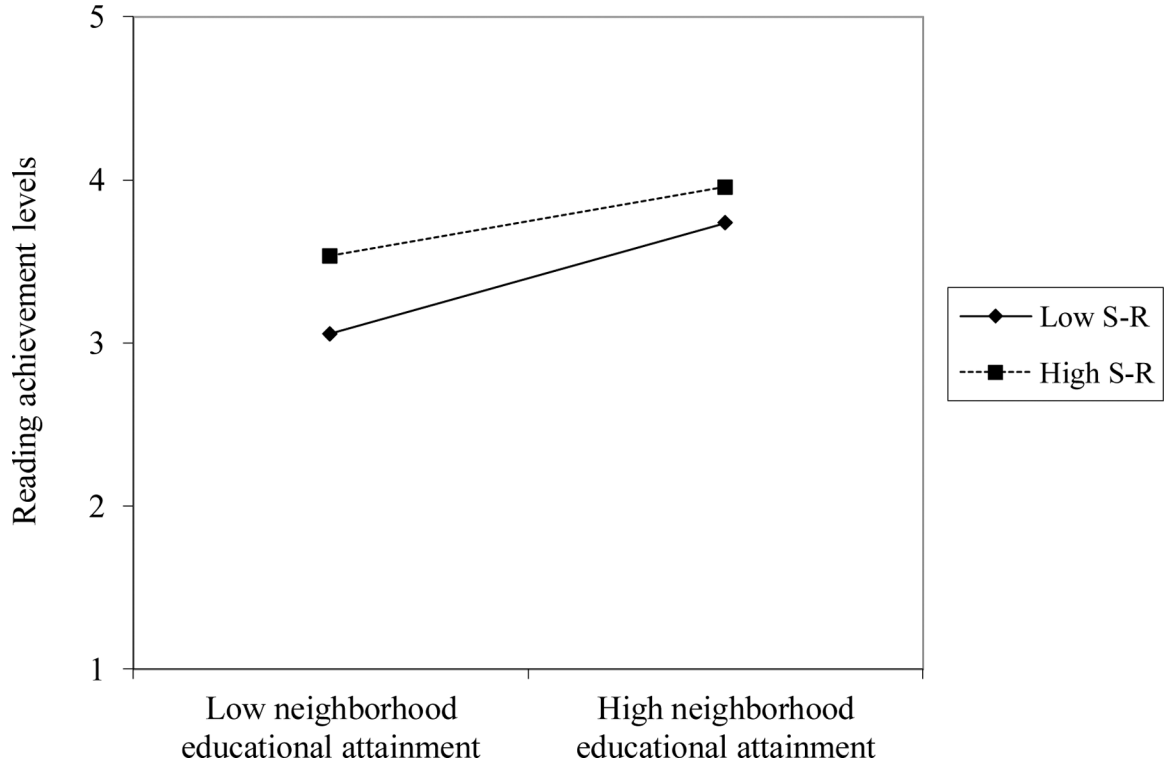

Figure 3.

Reading achievement levels as a function of neighborhood educational attainment (low: −1 *SD*, high: +1 *SD*) and self-regulation (low: −1 *SD*, high: +1 *SD*). Both slopes significant at $p < .0001$ level.

Table 1.

Demographics.

Demographic	Sample (*N* = 1,982)	Population (*N* = 460,760)
Sex		
Male	47.12%	51.38%
Female	52.88%	48.62%
Race/ethnicity[a]		
White	52.15%	51.34%
Black	23.14%	25.56%
Hispanic[b]	14.87%	15.04%
Asian	3.47%	2.80%
American Indian	2.09%	1.32%
Pacific Islander	0.20%	0.10%
Multiracial	13.18%	3.83%
Economically disadvantaged[c]		
No	54.64%	44.65%
Yes	45.05%	55.35%

Note.

[a]Multiracial mutually exclusive for population only. Sample totals > 100% for comparison with population.

[b]5.77% identified as Hispanic, missing race. *n* = 24 missing race, non-Hispanic.

[c]*n* = 11 missing economic disadvantage data.

Table 2.

Regression model predicting self-reported past-year grades.

Predictors	*B* (*SE*)	95% *CI*	*t*	*p*	R^2	*F*-change
Step 1: Covariates						
Age	−0.10 (0.03)	[−0.17, −0.03]	−2.92	.004		
Sex[a]	0.39 (0.07)	[0.24, 0.54]	5.23	< .0001	.020	
Race/ethnicity[b]					.106	30.03***
Step 2: Context						
Subjective SES	0.15 (0.05)	[0.06, 0.24]	3.18	.002		
Economic disadvantage	−0.53 (0.08)	[−0.69, −0.37]	−6.55	< .0001		
Gini coefficient	−0.42 (0.58)	[−1.56, 0.71]	−0.73	.47		
Neighborhood educational attainment	0.78 (0.19)	[0.42, 1.15]	4.17	< .0001		
Household chaos	−0.40 (0.06)	[−0.51, −0.29]	−7.29	< .0001		
					.196	41.65***
Step 3: Self-regulation	1.30 (0.09)	[1.12, 1.48]	14.14	< .0001		
					.274	200.06***
Interactions						
Subjective SES × S-R	−0.12 (0.12)	[−0.37, 0.12]	−1.00	.32	.274	1.26
Economic disadvantage × S-R	0.06 (0.19)	[−0.31, 0.43]	0.34	.74	.274	0.13
Gini coefficient × S-R	0.55 (1.59)	[−2.57, 3.68]	0.35	.73	.274	0.14
Neighborhood educational attainment × S-R	−1.43 (0.42)	[−2.26, −0.60]	−3.38	.001	.278	11.09**
Chaos × S-R	0.22 (0.15)	[−0.07, 0.52]	1.47	.14	.275	3.03

Note. $N = 1878$.

[a]Sex coded 0 = *male*, 1 = *female*.

[b]ΔR^2 for the set of race variables = .086.

*$p < .01$,

**$p < .001$,

***$p < .0001$.

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Table 3.

Regression model predicting educational aspirations.

Predictors	*B* (*SE*)	95% *CI*	*t*	*p*	R^2	*F*-change
Step 1: Covariates						
Age	0.03 (0.02)	[−0.01, 0.07]	1.28	.20		
Sex	0.18 (0.05)	[0.09, 0.28]	3.70	.0002	.008	
Race/ethnicity					.017	2.85**
Step 2: Context						
Subjective SES	0.06 (0.03)	[−0.002, 0.13]	1.89	.06		
Economic disadvantage	−0.17 (0.06)	[−0.28, −0.06]	−2.96	.003		
Gini coefficient	0.41 (0.41)	[−0.40, 1.22]	0.99	.32		
Neighborhood educational attainment	0.44 (0.13)	[0.18, 0.70]	3.26	.001		
Household chaos	−0.24 (0.04)	[−0.32, −0.16]	−6.10	< .0001		
					.064	18.80***
Step 3: Self-regulation	0.34 (0.07)	[0.20, 0.47]	4.89	< .0001		
					.076	23.88***
Interactions						
Subjective SES × S-R	0.12 (0.09)	[−0.04, 0.29]	1.45	.15	.077	2.26
Economic disadvantage × S-R	−0.36 (0.13)	[−0.62, −0.11]	−2.83	.005	.080	7.88*
Gini coefficient × S-R	1.61 (1.13)	[−0.60, 3.82]	1.43	.15	.077	2.08
Neighborhood educational attainment × S-R	0.16 (0.32)	[−0.47, 0.79]	0.49	.62	.076	0.24
Chaos × S-R	−0.03 (0.09)	[−0.21, 0.16]	−0.27	.79	.076	0.07

Note. $N = 1884$.

[a] Sex coded 0 = *male*, 1 = *female*.

[b] ΔR^2 for the set of race variables = .011.

* $p < .01$,

** $p < .001$,

*** $p < .0001$.

Table 4.

Regression model predicting math achievement level.

Predictors	*B* (*SE*)	95% *CI*	*t*	*p*	R^2	*F*-change
Step 1: Covariates						
Age	−0.29 (0.04)	[−0.37, −0.21]	−7.32	< .0001		
Sex[a]	0.07 (0.08)	[−0.07, 0.22]	0.98	.33	.038	
Race/ethnicity[b]					.151	31.63***
Step 2: Context						
Subjective SES	0.09 (0.05)	[−0.004, 0.18]	2.05	.04		
Economic disadvantage	−0.54 (0.09)	[−0.69, −0.39]	−6.94	< .0001		
Gini coefficient	−0.50 (0.57)	[−1.61, 0.62]	−0.87	.38		
Neighborhood educational attainment	1.34 (0.19)	[0.98, 1.71]	7.22	< .0001		
Household chaos	−0.16 (0.05)	[−0.27, −0.06]	−3.00	.003		
					.253	38.36***
Step 3: Self-regulation	0.69 (0.09)	[0.51, 0.87]	7.47	< .0001		
					.282	55.86***
Interactions						
Subjective SES × S-R	−0.00 (0.11)	[−0.21, 0.21]	−0.02	.98	.282	0.00
Economic disadvantage × S-R	0.01 (0.18)	[−0.34, 0.36]	0.06	.95	.282	0.00
Gini coefficient × S-R	2.58 (1.35)	[−0.06, 5.62]	1.92	.06	.283	2.80
Neighborhood educational attainment × S-R	−0.28 (0.42)	[−1.11, 0.55]	−0.66	.51	.282	0.40
Chaos × S-R	−0.01 (0.13)	[−0.28, 0.27]	−0.04	.97	.282	0.00

Note. $N = 1422$.

[a]Sex coded 0 = *male*, 1 = *female*.

[b]ΔR^2 for the set of race variables = .113.

*$p < .01$,

**$p < .001$,

***$p < .0001$.

Table 5.

Regression model predicting reading achievement level.

Predictors	*B* (*SE*)	95% *CI*	*t*	*p*	R^2	*F*-change
Step 1: Covariates						
Age	−0.12 (0.03)	[−0.18, −0.07]	−4.47	< .0001		
Sex[a]	0.20 (0.06)	[0.09, 0.32]	3.37	.0008	.017	
Race/ethnicity[b]					.140	44.60***
Step 2: Context						
Subjective SES	0.09 (0.04)	[0.02, 0.16]	2.46	.01		
Economic disadvantage	−0.45 (0.06)	[−0.57, −0.33]	−7.14	< .0001		
Gini coefficient	−1.31 (0.45)	[−2.20, −0.42]	−2.90	.004		
Neighborhood educational attainment	1.33 (0.15)	[1.05, 1.62]	9.12	< .0001		
Household chaos	−0.16 (0.04)	[−0.24, −0.07]	−3.67	.0003		
					.249	54.35***
Step 3: Self-regulation	0.47 (0.07)	[0.32, 0.61]	6.24	< .0001		
					.265	38.90***
Interactions						
Subjective SES × S-R	0.01 (0.09)	[−0.17, 0.19]	0.14	.89	.265	0.02
Economic disadvantage × S-R	0.15 (0.14)	[−0.13, 0.43]	1.02	.31	.265	1.07
Gini coefficient × S-R	0.61 (1.11)	[−1.57, 2.79]	0.55	.58	.265	0.25
Neighborhood educational attainment × S-R	−0.85 (0.31)	[−1.47, −0.24]	−2.71	.007	.267	6.03*
Chaos × S-R	−0.08 (0.11)	[−0.28, 0.13]	−0.72	.47	.265	0.53

Note. $N = 1880$.

[a]Sex coded 0 = *male*, 1 = *female*.

[b]ΔR^2 for the set of race variables = .123.

*$p < .01$,

**$p < .001$,

***$p < .0001$