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Associations Between Preschool Cognitive and Behavioral Skills and College Enrollment: Evidence from the Chicago School Readiness Project

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Abstract

The current paper examines associations between preschool cognitive and behavioral skills and indicators of college enrollment in a sample (n = 379) of primarily Black and Hispanic youth growing up in low-income areas of Chicago. Although we found that most early cognitive and behavioral skills were only weakly or moderately related to later college enrollment, a rating of preschool attention and impulsivity control was a relatively strong predictor. Across most models tested, attention and impulsivity control, executive functioning, and effortful control produced predicted probabilities that were similar in magnitude, or larger, than the effects produced by early math and literacy. There was no indication that early behavioral difficulties were substantive predictors of college enrollment. These descriptive findings suggest that in a low-income sample of children, some early cognitive capabilities related to attention and EF predict longer-term college enrollment. We discuss implications for developmental theory and suggest that caution should be applied when projecting likely effects of early skill-focused interventions.

Keywords: Self-regulation, early childhood education, early skills, longitudinal, college enrollment

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Introduction

Given the strong relation between college attainment and lifelong outcomes (e.g., increased earnings, better health, social costs reduction), researchers and policy makers continue to show substantial interest in understanding how early educational experiences influence children's participation in postsecondary education (McMahon, 2009). In the past few decades, this interest has extended to early childhood education, as several studies have tracked whether children's participation in early educational programs predicts adult educational attainment. Recent non-experimental analyses have suggested that enrollment in early childhood programs, such as the Child-Parent Center Program and Head Start, can lead to an increased likelihood of graduating from high school, attending college, and having a college degree by early adulthood (Garces et al., 2002; Ou & Reynolds, 2008; Reynolds et al, 2018; but see Pages et al., 2020 for contradictory evidence on Head Start). While these encouraging program effects have spurred large government investment in early childhood programs, more work is needed to understand the underlying mechanisms that contribute to the positive link between early childhood program participation and later college attainment. The current study seeks to examine the connection by examining links between a host of early child cognitive and behavioral skills and measures of early adult educational outcomes in a sample of primarily Black and Hispanic children growing up in high-poverty areas of Chicago.

Previous longitudinal correlational research has established that early skills measured at school entry strongly predict later educational success seen at middle childhood (Duncan et al., 2007). Indeed, these findings have contributed to substantial enthusiasm for the theory that early skills are foundational to later outcomes (i.e., "skills-beget-skills"). Following the model of Duncan et al. (2007), a large body of longitudinal research has shown that early child cognitive and behavioral skills are strong predictors of a child's developmental trajectories and school achievement. For example, children who enter kindergarten with number recognition skills are more likely to succeed in formal mathematics instruction (Entwisle et al., 2005; Watts et al., 2014). Children who enter with high levels of dysregulated and disrupted behavior tend to stay less engaged during school, thereby detracting from positive learning opportunities, which often leads to worse academic performance (Raver et al, 2007). Most notably, these weaknesses in behavioral regulatory skills have also been shown to be strong predictors of key adult outcomes, including health and economic attainment (Moffitt et al., 2011), while mastery of early numeracy skills at 4.5 years of age has been shown to predict college enrollment (Davis-Kean et al., 2021).

Taken together, the results of longitudinal skills research and the program effects on later educational attainment suggest that early educational programs should promote early cognitive and behavioral skill development, and these investments should lead to long-lasting effects on children's achievement trajectories. However, more recent evidence on academic skill development has suggested that longitudinal correlational studies may have difficulty projecting the likely outcomes of educational interventions (Bailey et al., 2018; Watts, 2020). Bailey et al. (2014) demonstrated that longitudinal associations between measures of mathematics achievement likely resulted from persistent sources of inter-individual stability that skill-focused interventions may be unlikely to alter. Moreover, accumulating early intervention evidence seems to suggest that longer-run impacts on attainment might arise even when immediate impacts on cognitive skills are not observed (Gray-Lobe et al., 2021). The lack of theoretical clarity regarding the ways early skill development might lead to longer-run outcomes suggests more research is needed to understand the role early child behavioral and cognitive capacities play in predicting eventual educational attainment.

Early Cognitive and Behavioral Skills

Among the domains of early skills often targeted by early intervention programs, academic skills have received the most attention in the longitudinal literature. This is unsurprising given that these skills provide the conceptual foundations upon which later learning is built. Indeed, correlational research (Duncan et al., 2007) and developmental theory (Siegler & Lortie-Forgues, 2014) suggests that early number sense supports the mastery of more complex mathematical concepts and problem-solving skills. Likewise, early reading and language skills have also been shown to predict later school success, as early reading and language achievement enables students to comprehend more complex texts during later schooling (Scarborough, 2001; Snow et al., 1998; Whitehurst & Lonigan, 1998). Intuitively, early skills may also allow students to have greater opportunities to participate in learning, breeding potential positive engagement with teachers and peers.

Surprisingly, few studies have explicitly studied the relative connections between early preschool skills and later college attainment, especially in high-risk samples. Longitudinal studies that examine early academic predictors tend to focus on later periods of childhood (e.g., kindergarten or elementary school; Dynarski et al., 2013; Entwisle et al., 2005; Lesnick et al., 2010; Magnuson et al., 2016). One exception is Davis-Kean and colleagues' (2021) analysis using the Study of Early Child Care and Youth Development (SECCYD) data. Their analysis, which drew on a sample of largely white middle-class children, found that mastery of three early numeracy skills at 4.5 years of age strongly predicted college enrollment in early adulthood. These findings seem to contradict an earlier finding by Entwisle and colleagues (2005). In an analysis of a cohort of children in Baltimore, in which approximately half the students were Black and most qualified for free or reduced-price lunch, they found that a composite of first grade reading and math test scores did not significantly predict enrollment in two-year colleges or four-year colleges (Entwisle et al., 2005).

Other key early skills, like self-regulation and executive function, have also been targeted by longitudinal studies as a result of their perceived theoretical importance in educational attainment. In theory, if a student can regulate their attention and impulses in the classroom, then they will have increased learning opportunities and, in turn, develop better mastery of content and higher achievement (see Blair & Raver, 2015). Indeed, some correlational work has reinforced this theory, as attention has been found to predict later achievement, even when controlling for demographic variables and prior academic performance (Barriga et al., 2002; Duncan et al., 2007; Howse et al., 2003). In a recent meta-analytic review, results from 55 meta-analyses provided evidence that self-regulation measured at age 4 was positively associated with social competency, school engagement and academic performance, while negatively associated with behavioral problems in middle childhood and early adolescence (Robson et al., 2020).

However, longitudinal studies that examine early behavioral predictors of college attainment also tend to focus on middle childhood (Currie & Stabile, 2006; Magnuson et al., 2016; Vitaro et al., 2005), and mixed findings have been reported across this literature. For example, Moffitt and colleagues' (2011) highly cited longitudinal study found that an index of measures of behavioral and attention problems (called "poor self-control") aggregated across multiple periods of childhood predicted a host of adult outcomes in New Zealand children. In contrast, Magnuson et al. (2016), using the National Longitudinal Survey of Youth (NLSY), which contained a diverse sample that included Black, Hispanic, and low-income youth, found that attention and impulsivity control problems during middle childhood did not significantly predict college attendance by age 20 and 21, while behavioral problems such as antisocial behaviors did.

Examinations of direct assessments of early child self-regulation have also produced somewhat mixed findings. In a study using longitudinal data from the Colorado Adoption Project (CAP), McClelland and colleagues (2013) found that attention span-persistence at age 4 had a positive and significant effect on college completion by age 25 for a sample of primarily White middle-class children. More recently, Ahmed and colleagues (2021) used the SECCYD to examine how an aggregated measure of early executive function, measured via direct-child assessments using cognitive tasks, predicted later adult outcomes. They found a moderate, positive association between executive function and educational attainment (with null effects reported for adult health). Yet, recent work on gratification delay found that success on the Marshmallow Test during early childhood was not predictive of adult economic attainment across multiple indicators for the relatively privileged set of children who participated in the original Marshmallow Test studies (Benjamin et al., 2020).

Current Study

Although prior research has provided some evidence regarding the long-run connections between early cognitive and behavioral skills and early adult attainment, the mixed findings suggest that more empirical work could provide further theoretical clarity. Moreover, many studies in the previous literature (e.g., Benjamin et al., 2020; Davis-Kean et al., 2021; Moffitt et al., 2011) have contained samples with limited diversity, which limits the application of existing evidence to policy discussions given that educational interventions often target children from low-income communities. We have long known that poverty creates an inequitable learning environment with less learning opportunities and lower rates of academic success (Duncan & Brooks-Gunn, 1997). Thus, it is crucial for our field to understand whether the skills and capacities targeted by early programs develop into long-run trajectories that lead to higher levels of educational attainment in populations most in need of opportunity.

The current study relied on data from the Chicago School Readiness Project (CSRP), a federally-funded intervention geared toward increasing preschoolers' chances of success in school (see Raver et al., 2009; 2011), to examine long-run associations between the host of skills developed during the preschool years and indicators of college enrollment. This data allowed us the rare opportunity to observe how a broad set of early capacities shape a crucial indicator of adult attainment. Importantly, this work is undertaken in a sample of primarily Black and Hispanic children growing up in high-poverty areas of Chicago.

Using CSRP's longitudinal data, this study presents a new and rigorous analysis of a diverse sample to provide valuable and unique insights on the associations between early skills and college enrollment. We examined how preschool indicators of early math and literacy skills, behavior problems (externalizing and internalizing behaviors), attention and impulsivity control, executive functioning, and effortful control predict students' later enrollment in two- and four-year colleges. We examined several predictive models, including models that estimate the relation between gains in each capacity during preschool and later enrollment. This analysis was not pre-registered. Although we did not have strong a priori hypotheses regarding the relative strength of each predictor, we anticipated that preschool measures of academic skills (i.e., mathematics and reading) would be the strongest predictors of later college enrollment given past correlational research underscoring the importance of academic skills for school readiness (e.g., Duncan et al., 2007).

Method

Procedure and Sample

The CSRP was designed as a cluster-randomized control trial implemented in Head Start centers serving high-poverty Chicago neighborhoods. Initial recruitment occurred during fall of 2004 and 2005 (i.e., two cohorts; see Table 1 for school enrollment and age progression of the two cohorts), and longitudinal college enrollment data has been recorded through the spring of 2021. The original intervention aimed to improve children's emotional and behavioral adjustment via a range of services: teacher development, mental health clinicians for classrooms, stress-reduction workshops for teachers, and direct family services for children with substantial behavioral and emotional dysregulation issues. Although the current analysis does not report intervention impacts on college enrollment, the original intervention evaluation reported positive initial impacts on children's early cognitive skills and behaviors (Raver et al., 2009, 2011). During adolescence, children were re-randomized to a mindset intervention, which produced primarily null effects on measures of achievement and self-regulation (Gandhi et al., 2020). Current work is underway to estimate the impacts of both programs on adolescent development (see also Watts et al., 2018) and end-of-high school achievement.

A total of 411 CSRP students (approximately 68% of the original sample) consented to releasing educational administrative data, which provided researchers access to college enrollment data through the National Student Clearinghouse (NSC). We limited our analytic sample to 379 students (approximately 63% of the original sample) who had consent for NSC data and at least one non-missing spring skill or behavioral measure[1]. These 379 students (208 girls; mean age in January of preschool year: 4.35 years; SD= 0.61) served as the study sample. Approximately 66% of the students identified as Black and 27% as Hispanic. Most of the students lived in multi-child homes, and families were predominantly low-income with an average income-to-needs ratio of 0.69. Table 2 presents the descriptive statistics of the full list of child and family characteristics considered in the current analysis (see Table A1 in Online Supplement A for descriptive statistics of the study sample compared to the full CSRP sample).

Measures

Preschool cognitive and behavioral functioning. Six measures of preschool cognitive and behavioral functioning were assessed during the fall and spring of the preschool year. Measures were collected by master's level assessors who were trained by the CSRP team. Apart from teachers and teacher assistants who completed the measures on behavior problems, all were blind to students' initial treatment status. These same measures served as the primary indicators of the efficacy of the CSRP preschool intervention (see Raver et al., 2009; 2011), which were originally

[1] This study was declared exempt by the IRB for Teachers College, Columbia University (protocol 19-474).

collected to provide a broad assessment of students' school readiness capacities at the end of preschool. Table 2 presents descriptive statistics of the fall and spring measures of the various preschool skills for the three subgroups representing different enrollment types: any college enrollment, post-secondary four-year college enrollment, and no enrollment.

Early academic skills. Students' early math and early literacy skills were measured using scores from the National Reporting System (NRS) assessment. Early math skills were assessed using the 20-item Early Math Skills Test, which covered basic mathematical concepts such as addition and counting (Zill, 2003a). Early literacy skills were assessed using a shortened version of the 24-item Peabody Picture Vocabulary Task (PPVT; Dunn, & Dunn, 1997; Zill, 2003b) and a 26-item letter naming task (Raver et al., 2011). For Spanish or bilingual speakers, Test de Vocabulario en Imagenes Peabody (TVIP; Dunn et al., 1986) and a 30-item letter naming task was used. The PPVT and the TVIP asked children to point to a picture out of a group of four that corresponded with the stated vocabulary, while the letter naming task asked children to name the displayed letters. Because the English version and the Spanish version of the letter naming task differed in the number of items, total percentage correct was calculated instead of total items correct. Scores from literacy assessments were then standardized and averaged to form a literacy composite.

Behavioral problems. Behavior problems, an aggregated measure of externalizing (e.g., lying, argues, bullies) and internalizing behaviors (e.g., clings to adults, cries too much, demands attention), was measured using a combination of teacher and parent reports. In the fall of preschool, teachers and parents reported on students' behavioral problems using the Behavior Problem Index (BPI; Zill, 1990), a 28-item rating scale that asked the respondent to rate a specific behavioral problem on a scale from 0 to 2 (0 = *not true*, 1 = *sometimes true*, 2 = *very true or often true*). Following the National Longitudinal Youth Survey, this scale was summed into Internalizing (α = 0.75) and Externalizing (α = 0.89) subscales. Student subscale scores were standardized and averaged across both raters to create a fall externalizing behavior score and a fall internalizing behavior score. In the spring of preschool, teachers reported on students' behavioral problems using the BPI (Internalizing α = 0.80 and Externalizing α = 0.91) and the Caregiver-Teacher Report Form (C-TRF; Achenbach & Rescorla, 2001), a 100-item rating scale that asked the respondent to rate each behavior on a scale from 0 to 2 (0 = *not true*, 1 = *somewhat or sometimes true*, 2 = *very true or often true*). This scale was also summed into Internalizing (α = 0.91) and Externalizing (α = 0.96) subscales, and the subscale ratings were once again standardized and then averaged to create a spring externalizing behavior score and a spring internalizing behavior score. From here, we created the behavior problems composite by first verifying positive correlations between externalizing and internalizing behavior ratings for both the fall and the spring (*r* [569] = 0.69 for fall and *r* [547] = 0.65 for spring), and then averaging across to create a fall composite and a spring composite.

Cognitive regulation and effortful control. Finally, the CSRP assessed students' self-regulation using the Preschool Self-Regulation Assessment (PSRA; Smith-Donald et al., 2007). Executive functioning is an aggregated measure consisting of the Balance Beam (Maccoby et al., 1965; Murray & Kochanska, 2002) and Pencil Tap task (Blair, 2002; Diamond & Taylor, 1996), while effortful control is an aggregated measure consisting of three delay tasks: Toy Wait, Snack Delay, and Tongue Task (Murray et al., 2002.) To ensure rating and coding accuracy, 20% of the sample was double rated and coded by assessors. Interrater reliability was calculated, and the average Cronbach's alpha across PSRA tasks was 0.93 (Raver et al., 2011). Scores from these tasks were then standardized and aggregated to create a composite score for executive function and a composite score for effortful control. After the completion of the PSRA tasks, assessors completed a 28-item PSRA Assessor Report, which was adapted from the Leiter-R social-emotional rating scale (Roid & Miller, 1997) and the Disruptive Behavior-Diagnostic Observation Schedule coding system (DB-DOS; Wakschlag et al., 2005). This assessor report was taken to provide a global picture of children's emotions, attention and impulsivity control, and behavior throughout the assessor-child interaction of the PSRA. Assessors rated each item using a Likert scale ranging from 0 to 3 with anchor points specific to the item (e.g., 0 = *never* and 3 = *always*). As with Raver et al. (2011), 16 items across the PSRA assessor report were aggregated to generate a measure of attention and impulsivity control (α = 0.92 as reported by Raver et al., 2011).

College enrollment. We provided names and birthdates to NSC for 411 students, and NSC returned enrollment records for 215 students covering up to 11 semesters of enrollment (semester range covers from fall 2016 to spring 2021). By the spring of 2021, students in our study sample were estimated to be approximately 19.92 years old, on average (20.33 years for students in the first cohort and 19.38 years for students in the second cohort). Table 1 presents the timeline for both cohorts of students spanning from the preschool wave of the study through the current study. As Table 1 reflects, both cohorts had at least 2 academic years post high school graduation (assuming Head Start enrollment at age 4 and on-time high school graduation) to appear in our NSC data. For children who enrolled in Head Start at age 3, they would have had at least 1 year of postsecondary data if they spent two successive years in Head Start[2]. In the supplementary file, we provide details of analyses that examined whether our results might have been biased due to differences in student age, and we found little indication that this might have been the case.

Because participation in the NSC by colleges is voluntary and some individual students under the Family Educational Rights and Privacy Act (FERPA) opt out of reporting information to

[2] In the current sample, parent-reported birthdates during Head Start indicated that the vast majority of children included in the study were 3 or 4 years old during the fall of the pre-k study year (56% of the original sample was over 4 years old). However, we were concerned that the youngest children in Cohort 2 may have not had an opportunity to enroll in college during our observation window. The last cohort included in our data pull would have begun kindergarten in the fall of 2007 and graduated from high school in 2019-2020 school year (assuming on-time graduation; see Table 1). We calculated that based on an age-eligibility cutoff of September 1 for kindergarten enrollment, approximately 1% of the students in the current study sample of 379 would not have been age eligible to begin kindergarten in 2007. We also ran our most restrictive model (e.g., model 4) with these students removed from the sample. The results were consistent with our main analysis.

NSC for research purposes, enrollment coverage by NSC is imperfect (Dynarski et al., 2015). Nonetheless, as of Spring 2021, the overall postsecondary enrollment coverage reported by NSC is 96.9% of all institutions within the United States (most of the study sample matriculated to colleges in Illinois, which had 98.2% coverage; National Student Clearinghouse, 2021) and the UChicago Consortium on School Research has recently found the NSC data to be suitable for determining college enrollment (Nagaoka & Mahaffie, 2020).

Any College Enrollment. We first used the NSC data to generate a measure of "any college enrollment," which simply counted 199 students (52.51% of the study sample; n = 379) with enrollment record data from NSC as "enrolled" and the 180 students with no data from NSC as "not enrolled" in college. Thus, this broad measure of college enrollment contains any kind of college course taking that would arise in NSC records, including 2-year college enrollment and "dual enrollment" during high school.

Postsecondary Four-Year Institution. We next attempted to generate a more narrowly defined measure of college enrollment that restricted the students coded as "yes" to only those with postsecondary enrollment in a four-year institution. Four-year institutions, though not always, are often more selective than community colleges and are generally associated with better long-term student outcomes such as higher college completion rates and higher future earnings (Baum et al., 2013). For this measure, we merged NSC data with (i) graduation data from student reports, parent reports, and administrative records from Chicago Public Schools (CPS), and (ii) college classification data from the Integrated Postsecondary Education Data System (IPEDS) to filter enrollment based on various school types. It should be noted that some two-year colleges are coded in IPEDS as four-year colleges if they offer at least one bachelor's degree program. We also pursued an extensive data cleaning process to determine whether enrollment occurred after high school to set aside "dual enrollment" semesters. We describe this verification process in detail in

Online Supplement B, and Table 3 presents descriptive data on the various indicators that were used to generate our two overarching measures of college enrollment. In the current sample, we observed that 27.18% of adolescents had valid postsecondary enrollment in a four-year institution.

Analytic Approach

To test the strength of the association between preschool skills and college enrollment, we began by regressing each dependent variable on: (i) each individual measure of cognitive and behavioral functioning taken during the spring of preschool; and (ii) a control for treatment status and cohort:

$$Model\ 1: Outcome_{ij} = \beta_0 + \beta_1 X_{ij} + \pi_1 Tx_j + \lambda_1 Cohort_j + e_{ij}$$

where $Outcome_{ij}$ represents a given indicator of college enrollment for the *i*th child in Head Start site j. X_{ij} represents each of the spring measures of the preschool skills. Tx_j represents the control for preschool intervention status, and $Cohort_j$ represents the control for cohort. Importantly, β_1 captures the change in the log odds or the predictive probability of a student enrolling in college for models with the binary indicator of college enrollment as the outcome (we tested both logistic and linear probability models).

For the second model, we added a host of child and family characteristics assessed during the fall of the preschool year:

$$Model\ 2: Outcome_{ij} = \beta_0 + \beta_1 X_{ij} + \pi_1 Tx_j + \lambda_1 Cohort_j + \chi Child_{ij} + e_{ij}$$

where the parameters are defined as before, but $Child_{ij}$ represents a vector of child and family characteristics (see Table 2 for the full list). Next, we added the fall measures of the preschool skills ($Fall_{ij}$) as baseline measures of each skill, which allowed us to test how *gains* in each domain during the preschool year predicted college enrollment:

$$Model\ 3: Outcome_{ij} = \beta_0 + \beta_1 X_{ij} + \pi_1 Tx_j + \lambda_1 Cohort_j + \chi Child_{ij} + \Omega Fall_{ij} + e_{ij}$$

where β_1 can now be interpreted as the predicted effect of a 1-SD *gain* in a given child skill or behavioral domain during preschool on college enrollment. This model better controls for potential sources of omitted variables bias, as it limits any unobserved confounders to variables that cause *changes* in a given preschool skill and later college enrollment.

Finally, in our "preferred models," we added Head Start site fixed effects ($\sum_{j=1}^{18} \gamma\, Site_j$) to account for the original cluster-randomization design and for any selection factors that could influence a family's decision to enroll in each Head Start center:

$$Model\ 4: Outcome_{ij} = \beta_0 + \beta_1 X_{ij} + \chi Child_{ij} + \Omega Fall_{ij} + \sum_{j=1}^{18} \gamma\, Site_j + e_{ij}$$

where β_1 can now be interpreted as the within-site effect of a 1-SD gain in a given skill or behavioral domain on later enrollment. If characteristics of Head Start sites largely drive the prediction between a given child skill and later enrollment (e.g., differences in curricula, teacher training, etc.), then we would expect to see relations between a given skill and later enrollment decrease when Head Start site fixed effects are controlled.

As we describe below, we also explored a "competing" model that entered the six early skill and behavioral domains into the same regression, which tests the relative contribution of each domain to later enrollment. This competing model examines the degree to which each respective domain might provide a unique contribution to later college enrollment, controlling for one's ability across the other domains. For all five models, we adjusted standard errors for clustering at the site level (though we also tested models that used non-clustered SEs, and significance levels were nearly unchanged).

As mentioned above, because college enrollment outcomes were binary indicators, we present enrollment model results from logistic regression in our main analyses. These models include coefficients transformed to odds-ratios, and 95% confidence intervals are reported for each estimate. In Online Supplement A, we include the same models run as “linear probability models” (LPMs), allowing us to interpret coefficients as changes in probabilities.

For the analytic sample of 379 students, we conducted missing data analysis to determine if any missing values were missing at random on the main predictors and controls. The results from these tests are described in Online Supplement A. To account for missing data for the study sample, we used multiple imputation with the spring of preschool measures, fall of preschool measures, and demographic controls included in the imputation model (i.e., see Table 2). For the models shown in our main tables, we did not impute on the dependent variables (though we did test imputation on the dependent variables, and results are displayed in Online Supplement E). For multiple imputation, we generated 25 multiple imputed datasets using the Markov Chain Monte Carlo procedure in Stata 16.0.

Results

Table 2 presents means, standard deviations, and p-values for our key analysis measures and control variables by enrollment type. Covariates include student demographic characteristics and family-life variables, which did not strongly correlate with either of our college enrollment outcomes (r [379] < |0.29|). A potential explanation for this result is the relative lack of heterogeneity in SES characteristics for the current sample, as all children were attending Head Start centers in socioeconomically disadvantaged areas of Chicago. To test for differences among participants who did and did not enroll in college, we regressed each of the predictors and control variables on college enrollment. The resulting p-values are presented in Table 2.

As Table 2 reflects, we observed statistically significant differences in gender, immigrant status, and mother’s education between college enrollees and those who did not enroll. College enrollees were approximately 13 percentage points more likely to be girls than boys ($p = 0.033$) and approximately 11 percentage points more likely to be immigrants ($p = 0.040$). Further, college enrollees were more likely to have mothers who either attained a bachelor's degree (6 percentage points, $p = 0.019$) or attended some college (8 percentage points, $p = 0.034$). And as expected, we saw that students who enrolled in college tended to have higher levels of fall preschool skills and less behavioral problems (a point we return to below).

Table 3 presents the analytic sample by category of college enrollment. The first major category, the "Any Enrollment" column, presents the number of students who had any enrollment records for various types of college enrollment, including dual enrollment while in high school. The sub-categories of college enrollment were calculated to be mutually exclusive for this table, and students were grouped based on their most advanced enrollment behavior. For example, the 7.92% of students in the "dual enrollment" group were students who had dual enrollment data as their *only* type of college enrollment. Thus, we observed that approximately 17% of the sample only ever enrolled in a 2-year school, and approximately 28% of the sample ever enrolled in a 4-year college (these students may have also had 2-year enrollment at some point in the observation window). The second column presents the sub-categories of enrollment included in our "Post-secondary Four-year Enrollment" indicator, and as Table 3 reflects, students who only ever enrolled in a 2-year school or those who only had dual enrollment in high school were set to "zero" on this measure. Three additional students were removed from this category because they did not meet the required enrollment seat time (at least 75%) per semester.

Table 4 presents the correlation between the two college enrollment outcomes ("Any College Enrollment" and "Post-secondary Four-year College Enrollment") and the spring preschool skills scores. All six skill measures significantly correlated with one another, with magnitudes ranging from $|0.17|$ to $|0.79|$ (the highest correlation observed was between preschool math and reading). Attention and impulsivity control significantly correlated with both college enrollment outcomes (r [353] = 0.23 for "Any College Enrollment," $p < 0.001$; r [353] = 0.14 for "Post-secondary Four-year College Enrollment," $p = 0.007$), while effortful control significantly correlated with "Any College Enrollment" (r [352] = 0.15, $p = 0.006$).

Logistic Models: College Enrollment

Table 5 presents odds ratios from our key models, with each spring of preschool skill considered as a predictor and a binary indicator of any college enrollment entered as the outcome. In Column 1, we began by treating each predictor separately with only treatment and cohort controlled (i.e., *Model 1*) before stepping in family background measures in Column 2 (i.e., *Model 2*). In Column 3, we added the fall measure of each respective predictor as a control (i.e., *Model 3*), and in Column 4, we added Head Start site fixed effects (i.e., *Model 4*). Column 5 considers all predictors simultaneously (with the *Model 4* specification used for control variables).

Across the domains considered, we found the PSRA observer-rating of attention and impulsivity control to be the strongest and most consistent predictor of later college enrollment. In *Model 1*, a 1-SD increase in preschool attention and impulsivity control predicted an increase in the odds of later college enrollment by a factor of 1.58 ($p < 0.001$). In other words, for a 1-SD increase in attention, the odds of college enrollment increased by 58%. This increase in odds fell slightly to 50% when demographic controls were included ($OR = 1.50$, $p = 0.002$). In Column 3, we considered how gains in attention and impulsivity control over the preschool year predicted later enrollment. We again found that gains were significantly predictive, with a 1-SD increase in attention predicting a 38% increase in the odds of enrollment ($OR = 1.38$, $p = 0.021$). Interestingly, when Head Start site fixed effects were added (Column 4), the prediction was slightly larger ($OR = 1.51$, $p = 0.017$), indicating that differences between Head Start sites did not account for the relation between attention and later enrollment. Finally, our exploratory model, which considered all of the spring preschool predictors simultaneously (Column 5), again indicated that attention and impulsivity control was an important predictor of later enrollment conditional on gains in the other preschool skills (*OR* = 1.50, $p = 0.029$). To help better contextualize these effects, we present results from linear probability models in Online Supplement Table A2. Here, we found that a 1-SD gain in preschool attention and impulsivity control was associated with an 8 percentage-point increase ($p = 0.025$) in the probability of enrollment (i.e., *Model* 4).

While early math skills, early literacy skills, executive functioning, and effortful control also demonstrated positive prediction for the "Any College Enrollment" outcome when only treatment and cohort were included as controls, their effects were smaller in magnitude and the only statistically significant predictor from this group was effortful control (see Table 5). However, this prediction did not hold in the "gains" model (i.e., *Model 4*) for effortful control, and the measure of executive function produced a statically significant prediction only in this model.. Neither were significant in the model with all of the spring skill measures included. We found no indication that behavioral problems predicted later college enrollment.

In Table 6, we extended our results by including the binary indicator of four-year postsecondary college enrollment as the outcome. Across these models, we again observed attention and impulsivity control to be the strongest and most consistent predictor. In our preferred model (i.e., *Model 4*), a 1-SD increase in preschool attention and impulsivity control predicted an increase in the odds of post-secondary four-year college enrollment by a factor of 1.47 ($p = 0.022$), in other words, a 47% increase in odds of enrollment. As Online Supplement Table A3 shows, the linear probability model suggested that a 1-SD increase in preschool attention and impulsivity was associated with a 6 percentage-point increase ($p = 0.020$) in the probability of enrollment (i.e., *Model* 4). Once again, we observed that early math skills, early literacy skills, executive functioning, and effortful control positively predicted post-secondary four-year college enrollment with smaller and largely non-significant effects. From this group, only effortful control and early literacy skills were statistically significant predictors, but the significance did not hold once controls were included. Behavioral problems were negatively related to later enrollment, but the prediction was non-significant. As opposed to the "Any College Enrollment" model, no single measure produced a statistically significant prediction when all of the spring preschool measures were considered simultaneously.

Additional Results

In the online supplemental file, we provide results from several supplementary models that were pursued to examine the robustness of our main results.

First, we examined sensitivity of our results to differences in student age. Because our data contained two cohorts of students, we recognized that older students would have more opportunity to enroll across our observation window than younger students. However, it should be noted that all of our models with control variables controlled for student age in preschool (i.e., these models controlled for within-cohort variation in age), and we did not observe a significant difference in age between college enrollees and non-enrollees on the "Any Enrollment" indicator (p = 0.276; see Table 2). As we detail in Online Supplement C, we did not find indications that differences in age attenuated our results, as we found no interactions between the preschool skills and student age, nor did we find that predictions were systematically stronger in older students when we split the sample on age.

Next, we ran a series of models examining how the CSRP preschool intervention might have affected the predictive relations we report here. Because the preschool intervention targeted the skills that served as our key predictors, we tested whether predictions might have been attenuated due to random assignment to the treatment. As we detail in Online Supplement C, we saw no indication that predictions to college enrollment significantly differed between the preschool treatment and control groups. We also tested models that used fall (i.e., intervention baseline) measures of preschool skills and behaviors, and results for attention and impulsivity control were

were largely similar to those reported in our key tables (though we found more predictive validity for fall behavioral problems and effortful control).

In Online Supplement D, we present findings from supplementary models that used a survey-based measure of college preparedness as the predicted outcome. We saw no significant predictions for any of the early skills when controls were included. Although we originally hoped that this survey-based measures of college preparedness would serve as an additional key outcome in our analyses, we found more evidence that student age and treatment status biased predictions. Thus, we only present these results in the supplemental file.

Finally, because our sample was limited to students who were consented for the release of administrative data at adolescent follow-up waves and those with at least one spring measure of preschool skills, we also tested if results were consistent with adjustments for attrition. In Online Supplement E, we present results from key models that used multiple imputation to adjust for missing data on college enrollment due to study attrition, which allowed us to recover the full sample (n = 602), and results were again similar to those shown in our key tables.

Discussion

There is continued interest in the field regarding the connections between early childhood skills and later adult outcomes, however we need more research to help us understand the long-term developmental trajectories stemming from early skill development, especially for children who face substantial economic disadvantages. Past research consistently highlights a predictive relationship between these skills and children's later educational success, which in turn is linked to future adult attainment (Ahmed et al., 2021; Moffitt et al., 2011). However, research has also shown that poverty heavily affects the cognitive and behavioral developmental trajectories of young children (Duncan & Brooks-Gunn, 1997). Our study attempted to test the links between early cognitive and behavioral skills and a key indicator of adult attainment, college enrollment, in a sample of children coming from homes taxed by the stresses of poverty.

We found that, overall, early indicators of behavioral and cognitive skills were not strongly predictive of later college enrollment. The notable exception to this pattern was the measure of attention and impulsivity control, which was a robust predictor of any college enrollment and enrollment in four-year schools. We found no significant relation between the measures of behavioral problems and college enrollment in our preferred models, and surprisingly, we found weaker-than-expected relations between early academic skills and later enrollment. The measures of executive function and effortful control fell somewhere in between, as these measures were predictive in some models, but not consistently so.

The lack of prediction for the measures of academic skills may be the most surprising finding, given that previous research has regularly demonstrated the strong relation between early academic achievement and later attainment (Davis-Kean et al., 2021), and other studies have found that academic skills correlate with later earnings (e.g., Ritchie & Bates, 2013; Watts, 2020). These findings could hold implications for both theory and practice in early childhood educational research. First, it could be the case that other factors simply matter much more for determining the college enrollment of children in high poverty neighborhoods. Indeed, structural barriers, such as access to financial aid (Dynarski & Scott-Clayton, 2013), may dwarf any potential effects of early skills on later enrollment patterns for minoritized students from heavily disadvantaged neighborhoods (Perna 2006; 2007). Work from Lee (2012), which used several nationally representative longitudinal datasets found that Black and Hispanic students from low-income backgrounds tend to be on the “college readiness trajectory” in math growth until third grade, after which they then begin to fall progressively behind despite early childhood intervention received.

This work may also suggest that early academic skills could be less predictive of attainment for low-income students if poverty continually disrupts their academic trajectories throughout school.

Second, these results could provide some further clarity for the mounting evidence that suggests that ECE programs may spur later attainment effects, even when impacts on achievement test scores are not detected (e.g., Gray-Lobe et al., 2021). Certainly, experimental work with robust causal identification is needed to better understand mechanisms between early programs and later adult outcomes, but our results suggest that changes in early academic skills may not be as crucial for later enrollment as previous work might suggest. If early gains in math and reading are not strongly predictive of later college enrollment in a sample of high-poverty children in regression models with controls, then it may be no surprise that impacts on test scores provide uncertain projections as to whether a given early program will have an effect on later educational attainment (but see Dynarski et al., 2013).

Given the possibility that structural barriers may weaken predictions between early skills and later enrollment for highly impoverished students, we ran post hoc tests that attempted to further examine the possibility that early academic skills were *less* predictive of later enrollment for the most impoverished students in the sample. In Online Supplement F, we detail results from models that tested interactions between each of our key predictors and an indicator of “deep poverty” in early childhood. This deep poverty indicator had been used in other analyses using the CSRP dataset (see Raver et al., 2009), and it was equal to “1” if a student’s mother had less than a high school degree, family income-to-needs ratio in early childhood was less than half the federal poverty threshold, and the mother reported working 10 or fewer hours per week. Interestingly, we found no consistent indication that the early academic skills were less predictive for children exposed to deep poverty during early childhood. However, it is important to note that our sample lacks substantial heterogeneity in socioeconomic status, as all of the children were recruited from

Head Start centers serving low-resource neighborhoods. Thus, these interactions could produce different results with more middle- and high-income peers in the sample.

Interestingly, the attention and impulsivity control rating was perhaps the most robust predictor of later college enrollment. There is empirical evidence that attention control increases with age, with the increase being especially large from early childhood to middle childhood (Raffaelli, Crockett, & Shen, 2005). In other words, it is likely that preschool children with high attention control relative to their peers continue to show comparatively higher levels of attention through middle childhood and adolescence. These earlier findings provide a potential explanation for the findings in our study: the attention skills observed in early preschool children sustain active engagement in learning past preschool, possibly including higher compliance and the ability to follow rules and expectations, thereby increasing the children's opportunities to learn and increasing their chances of readiness for college. These findings likely echo the well-cited self-control findings from Moffitt and colleagues (2011), though their self-control composite was assessed over multiple ages and included behavioral problems as well as ratings of inattention. Notably, a similar rating of preschool attention to the one used in the current sample was also found to be predictive of attainment in a study of largely White middle-class children (McClelland et al., 2013).

However, implications for early intervention are not clear. Indeed, although the initial evaluation of the CSRP intervention reported impacts on EF and attention (Raver et al., 2011), other EF-focused early interventions have reported more difficulty moving measures of these constructs (Nesbitt & Farran, 2021). Moreover, in the current analysis, our models with Head Start site fixed effects provided little indication that differences between Head Start sites could account for the predictive association between attention and later enrollment. Of course, the factors targeted by early interventions may not be captured by simply controlling for the Head Start site of enrollment. However, it should be noted that we also tested models that attempted to control for preschool classroom-level predictors of child outcomes to assess if classroom processes could also account for any relations between early skills and later enrollment, and we again found that these variables left our main predictions largely unchanged (results available upon request). Thus, the mechanisms that link early skill development to later college enrollment may have less to do with differences in early educational experiences and more to do with other persistent factors that shape children's early lives. In other words, successful early interventions may need to target the processes that lead to early differences in attention skills between children to have the most success (see Watts & Duncan, 2020).

Finally, looking across the models we tested, the effect for behavior problems was unremarkable, even when covariates were not included (though the fall behavioral problems measure was found to be predictive in models included in the appendix). While our measure of behavior problems is much narrower, these finding echoes what we have seen in past studies with broader measures and multiple assessors (e.g., Duncan et al., 2007; but see Moffitt et al., 2011). We found the lack of association between behavioral problems and later college enrollment to be reassuring given that: (i) behavior problems, which are often over penalized in black and brown student populations, tend to invoke consequential disruptions to learning, such as school suspensions, expulsions, or drop-out, which all hinder a student's chances of enrolling in college (Skiba et al., 2002); and (ii) some past studies have linked behavior problems during middle childhood to negative college attendance (Magnuson et al. 2016).

Limitations

There are several limitations to the present study. First, we measured college enrollment and not college persistence. Thus, it is not clear whether these patterns would hold if college degree attainment were used as the dependent variable. Indeed, college persistence remains a critical issue for low-income students, even among those who enroll in four-year institutions (Ciocca Eller &

DiPrete, 2018). Further, despite our careful work with the administrative data supplied to us by NSC (see Online Supplement B), we recognize that our measure could be limited by student age and availability of college enrollment data at the time of the study. However, other studies that have reported ECE impacts on college enrollment have also relied on NSC data with similar follow-up designs (e.g., Gray-Lobe et al., 2021). Second, as we have repeatedly noted, our sample of low-income children from Chicago was ethnically diverse, but not nationally representative. Thus, findings could differ in a study with more socioeconomic diversity. Third, because our sample size was limited, we often reported wide confidence intervals, which should be taken into account when interpreting any significant or null effects. Finally, our models were not derived from experimental variation. Thus, results should not be interpreted as causal effects.

Conclusion

Taken together, the results suggest that some early cognitive and behavioral skills do predict college enrollment among a sample of minoritized youth growing up in high poverty neighborhoods. Our measure of attention and impulsivity control was the strongest and most consistent predictor of later enrollment. Across the models reported here, attention and impulsivity control, executive functioning, and effortful control were similar in magnitude in predicted probabilities, and often larger than the effects produced by early math and early literacy. However, researchers should interpret these results with caution given that causal relationships have not been established, and there was some variability in the estimates within and across models. It is not clear whether an intervention that tries to target attention and impulsivity control would lead to improved college enrollment. Nevertheless, these descriptive results can provide useful information to those hoping to better understand how early capacities relate to crucial long-term outcomes.

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Table 1

Enrollment and Age Progression of CSRP Cohorts

	Cohort 1		**Cohort 2**	
	Normative Grade	**Normative Age**	**Normative Grade**	**Normative Age**
	(1)	**(2)**	**(3)**	**(4)**
School year (Sept. to Jun.)				
2004 – 2005	PreK	4		
2005 – 2006	K	5	PreK	4
2006 – 2007	1	6	K	5
2007 – 2008	2	7	1	6
2008 – 2009	3	8	2	7
2009 – 2010	4	9	3	8
2010 – 2011	5	10	4	9
2011 – 2012	6	11	5	10
2012 – 2013	7	12	6	11
2013 – 2014	8	13	7	12
2014 – 2015	9	14	8	13
2015 – 2016	10	15	9	14
2016 – 2017	11	16	10	15
2017 – 2018	12	17	11	16
2018 – 2019	Post-HS	18	12	17
2019 – 2020	Post-HS	19	Post-HS	18
2020 – 2021	Post-HS	20	Post-HS	19
On-time college enrollment	By 2018 – 2019		By 2019 – 2020	

Note. This table displays the two CSRP cohorts and their respective enrollment and age progressions assuming Head Start enrollment at age 4. Our final college enrollment data pull from National Student Clearinghouse was completed in April of 2021.

Table 2

Descriptive Statistics by Enrollment Classification

	College Enrollees	No College Enrollment	P-value of diff. for (1) vs (2)	Four-year Enrollees
	(1)	(2)	(3)	(4)
Child Skills and Behaviors from Head Start Spring (standardized)				
Early math skills	0.10 (0.98)	-0.08 (1.02)	0.187	0.08 (1.00)
Early literacy skills	0.07 (1.01)	-0.09 (0.99)	0.262	0.16 (1.03)
Behavior problems	-0.03 (1.00)	0.07 (1.00)	0.450	-0.06 (1.05)
Attention and impulsivity control	0.23 (0.75)	-0.20 (1.10)	<0.001	0.25 (0.74)
Executive functioning	0.08 (0.99)	-0.08 (1.01)	0.080	0.08 (0.89)
Effortful control	0.18 (0.85)	-0.12 (1.12)	0.007	0.20 (0.86)
Child Skills and Behaviors from Head Start Fall (standardized)				
Early math skills	0.12 (0.97)	-0.10 (1.03)	0.074	0.15 (1.01)
Early literacy skills	0.10 (1.04)	-0.09 (0.95)	0.145	0.25 (1.04)
Behavior problems	-0.09 (1.07)	0.14 (0.96)	0.035	-0.13 (1.00)
Attention and impulsivity control	0.25 (0.76)	-0.14 (1.08)	0.001	0.25 (0.75)
Executive functioning	0.03 (0.90)	-0.03 (1.02)	0.413	-0.01 (0.85)
Effortful control	0.21 (0.80)	-0.14 (1.00)	0.011	0.23 (0.77)
Child and Family Characteristics				
Female	0.61 (0.49)	0.48 (0.50)	0.033	0.60 (0.49)
Age at preschool midpoint	4.40 (0.59)	4.30 (0.63)	0.276	4.41 (0.57)
Child ethnicity (Black)	0.60 (0.49)	0.73 (0.44)	0.085	0.66 (0.48)
Child ethnicity (Hispanic)	0.34 (0.47)	0.20 (0.40)	0.061	0.29 (0.46)
Parent or child is immigrant	0.22 (0.41)	0.10 (0.31)	0.040	0.17 (0.38)
Mother attained B.A. or higher	0.11 (0.31)	0.05 (0.23)	0.019	0.12 (0.33)
Mother attended some college	0.31 (0.47)	0.24 (0.43)	0.034	0.32 (0.47)
Parent full-time employed	0.45 (0.50)	0.36 (0.48)	0.122	0.52 (0.50)
Income-to-needs ratio	0.74 (0.54)	0.64 (0.59)	0.084	0.81 (0.66)
N	199	180		103

Note. Means values are presented with standard deviations in parentheses. All fall and spring measures of child skills and behaviors were standardized across the original sample. To test for difference among participants who enrolled in college and did not enroll in college, each of the predictors and control variables was regressed on the “any college enrollment” dummy variable. The resulting p-values are presented in the “P-value” column. P-values less than 0.001 have been shown as “< 0.001.”

Table 3

Sample Categories by Type of Enrollment

	Any Enrollment n (% of analysis sample)	**Post-secondary Four-year Enrollment** n (% of analysis sample)
Dual enrollment while in high school	30 (7.92%)	0 (0.00%)
Two-year college	63 (16.62%)	0 (0.00%)
Inclusive four-year college	37 (9.76%)	36 (9.50%)
Selective four-year college	47 (12.40%)	46 (12.14%)
Highly selective four-year college	22 (5.80%)	21 (5.54%)
Total	**199 (52.51%)**	**103 (27.18%)**

Note: "Any Enrollment" presents the number of students who had any enrollment records for various types of college enrollment, including dual enrollment while in high school. The "analysis sample" is designated as any student who was approved for NSC data release and has at least one spring skills score (n = 379). "Post-secondary four-year enrollment" restricts the sample to only students who had verifiable four-year college enrollment after high school. 30 students with only dual enrollment during high school and 63 students with only two-year college enrollments were excluded. 3 additional students were excluded because they did not meet the required enrollment seat time per semester.

Table 4

Correlations Between Spring Preschool Skills and College Enrollment Outcomes

	Any College Enrollment	Post-secondary Four-year College Enrollment	Early Math Skills	Early Literacy Skills	Behavior Problems	Attention and Impulsivity Control	Executive Functioning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any college enrollment	1						
Post-secondary four-year college enrollment	0.58*** (n = 379)	1					
Early math skills	0.09 (n = 350)	0.04 (n = 350)	1				
Early literacy skills	0.08 (n = 350)	0.10 (n = 350)	0.79*** (n = 350)	1			
Behavior problems	-0.05 (n = 377)	-0.05 (n = 377)	-0.28*** (n = 348)	-0.22*** (n = 348)	1		
Attention and impulsivity control	0.23*** (n = 353)	0.14** (n = 353)	0.45*** (n = 350)	0.38*** (n = 350)	-0.26*** (n = 351)	1	
Executive functioning	0.08 (n = 352)	0.04 (n = 352)	0.54*** (n = 349)	0.55*** (n = 349)	-0.17** (n = 350)	0.37*** (n = 352)	1
Effortful control	0.15** (n = 352)	0.10 (n = 352)	0.32*** (n = 349)	0.26*** (n = 349)	-0.23*** (n = 350)	0.64*** (n = 352)	0.31*** (n = 352)

Note: "Any college enrollment" and "post-secondary four-year college enrollment" measures were created using April 2021 enrollment data from National Student Clearinghouse. *** p< 0.001, ** p < 0.01 * p < 0.05

Table 5

Associations Between Preschool Skills and the Indicator for Any College Enrollment (n = 379, M = 52.51%)

	Single Predictor Logit Regression				**Multiple Predictors Logit Regression**
	Model 1, OR (95% CI) (1)	Model 2, OR (95% CI) (2)	Model 3, OR (95% CI) (3)	Model 4, OR (95% CI) (4)	Model 5, OR (95% CI) (5)
Early math skills	1.20 (0.95,1.51)	1.08 (0.84,1.39)	1.03 (0.73,1.44)	1.10 (0.75,1.62)	0.73 (0.47,1.13)
Early literacy skills	1.20 (0.91,1.58)	1.14 (0.84,1.53)	1.14 (0.74,1.77)	1.35 (0.82,2.22)	1.66 (0.94,2.92)
Behavior problems	0.90 (0.69,1.17)	1.01 (0.77,1.32)	1.08 (0.81,1.43)	1.11 (0.81,1.53)	1.26 (0.89,1.78)
Attention and impulsivity control	1.58*** (1.29,1.93)	1.50** (1.16,1.93)	1.38* (1.05,1.82)	1.51* (1.08,2.11)	1.50* (1.04,2.17)
Executive functioning	1.18 (0.98,1.42)	1.15 (0.87,1.52)	1.21 (0.92,1.58)	1.34* (1.00,1.80)	1.12 (0.81,1.53)
Effortful control	1.32** (1.09,1.59)	1.25 (0.97,1.62)	1.13 (0.83,1.54)	1.25 (0.88,1.78)	1.06 (0.72,1.55)
Treatment and cohort	Inc.	Inc.	Inc.	Inc.	Inc.
Demographic controls		Inc.	Inc.	Inc.	Inc.
Preschool fall skills baseline			Inc.	Inc.	Inc.
Head Start site fixed effects				Inc.	Inc.

Note. Continuous variables (i.e., skills scores) were standardized using the aggregated mean and standard deviation. Any college enrollment outcome was binary. Odds ratios (OR) and 95% confidence intervals (CI) were generated from the log coefficients and standard error. All models control for treatment status and cohort year. + p<.10 * p< .05 ** p < .01 *** p < .001

Table 6

Associations Between Preschool Skills and the Indicator for Post-Secondary Four-year College Enrollment (n = 379, M = 27.18%)

	Single Predictor Logit Regression				**Multiple Predictors Logit Regression**
	Model 1, OR (95% CI) (1)	Model 2, OR (95% CI) (2)	Model 3, OR (95% CI) (3)	Model 4, OR (95% CI) (4)	Model 5, OR (95% CI) (5)
Early math skills	1.12 (0.86,1.44)	1.02 (0.75,1.38)	0.98 (0.73,1.33)	1.02 (0.74,1.41)	0.63 (0.37,1.07)
Early literacy skills	1.29* (1.01,1.66)	1.25 (0.89,1.75)	1.09 (0.72,1.64)	1.14 (0.74,1.76)	1.66 (0.85,3.25)
Behavior problems	0.88 (0.64,1.22)	0.93 (0.66,1.32)	1.00 (0.68,1.48)	0.97 (0.61,1.53)	1.07 (0.65,1.75)
Attention and impulsivity control	1.45** (1.10,1.91)	1.41* (1.07,1.86)	1.33* (1.00,1.78)	1.47* (1.06,2.05)	1.37 (0.88,2.13)
Executive functioning	1.11 (0.93,1.33)	1.08 (0.85,1.37)	1.19 (0.93,1.53)	1.27 (0.98,1.64)	1.11 (0.83,1.48)
Effortful control	1.29* (1.01,1.63)	1.27 (0.99,1.63)	1.14 (0.87,1.50)	1.22 (0.91,1.63)	1.10 (0.76,1.59)
Treatment and cohort	Inc.	Inc.	Inc.	Inc.	Inc.
Demographic controls		Inc.	Inc.	Inc.	Inc.
Preschool fall skills baseline			Inc.	Inc.	Inc.
Head Start site fixed effects				Inc.	Inc.

Note. Continuous variables (i.e., skills scores) were standardized using the aggregated mean and standard deviation. Post-secondary four-year college enrollment outcome was binary. Odds ratios (OR) and 95% confidence intervals (CI) were generated from the log coefficients and standard error. All models control for treatment status and cohort year. + p<.10 * p< .05 ** p < .01 *** p < .001