Developmental Psychology

ISSN: 0012-1649

https://doi.org/10.1037/dev0001546

Quality of Early Childcare and Education Predicts High School STEM Achievement for Students From Low-Income Backgrounds

Andres S. Bustamante, Vanessa N. Bermudez, Karlena D. Ochoa, Ashlee B. Belgrave, and Deborah Lowe Vandell
School of Education, University of California, Irvine

High-quality early childcare and education (ECE) has demonstrated long-term associations with positive educational and life outcomes and can be particularly impactful for children from low-income backgrounds. This study extends the literature on the long-term associations between high-quality caregiver sensitivity and responsiveness and cognitive stimulation (i.e., caregiving quality) in ECE settings and success in science, technology, engineering, and mathematics (STEM) in high school. Using the 1991 National Institute of Child Health and Human Development Study of Early Child Care and Youth Development ($n = 1{,}096$; 48.6% female; 76.4% White, 11.3% African American, 5.8% Latine, 6.5% other), results demonstrated that caregiving quality in ECE was associated with reduced disparities between low- and higher-income children's STEM achievement and school performance at age 15. Disparities in STEM school performance (i.e., enrollment in advanced STEM courses and STEM grade point average) and STEM achievement (i.e., Woodcock–Johnson cognitive battery) were reduced when children from lower-income families experienced more exposure to higher caregiving quality in ECE. Further, results suggested an indirect pathway for these associations from caregiving quality in ECE to age 15 STEM success through increased STEM achievement in Grades 3 through 5 (ages 8–11 years). Findings suggest that community-based ECE is linked to meaningful improvements in STEM achievement in Grades 3 through 5 which in turn relates to STEM achievement and school performance in high school, and caregiving quality in ECE is particularly important for children from lower-income backgrounds. This work has implications for policy and practice positioning caregivers' cognitive stimulation and sensitivity in ECE settings across the first 5 years of life as a promising lever for bolstering the STEM pipeline for children from lower-income backgrounds.

Public Significance Statement
High-quality caregiving, that is emotionally responsive and cognitively stimulating, in the first 5 years of life is linked to STEM achievement and school success at age 15, and this relation is facilitated through increased STEM achievement in Grades 3–5. Further, this link is particularly strong for children from low-income families who benefit uniquely from exposure to high-quality early childcare and education. This work informs policy conversation around investing in high-quality early childcare and education for children from underserved communities.

Keywords: early childcare and education, STEM achievement, longitudinal research, caregiving quality in early childhood education, children from low-income backgrounds

One of our nation's largest policy efforts to support the development of children from low-income families is expanding access to early childcare and education with high caregiving quality (i.e., cognitively stimulating interactions and a rich language environment, as well as a warm, emotionally supportive, and responsive style of caregiving) in the first 5 years of life. Federal programs

Andres S. Bustamante https://orcid.org/0000-0002-7678-816X
A cooperative agreement (5 U10 HD027040) between the study investigators that included Deborah Lowe Vandell and the Eunice Kennedy Shriver National Institute of Child Health and Human Development supported the design and data collection of the Study of Early Child Care and Youth Development (SECCYD) from birth through age 15 years. Andres S. Bustamante was supported by a grant from the American Educational Research Association (AERA) which receives funds for its AERA Grants Program from the National Science Foundation (NSF) under award NSF-DRL 1749275. Opinions reflect those of the author and do not necessarily reflect those of AERA or NSF. Finally, we thank the study participants for their willingness to be a part of this longitudinal follow-up of a project that began shortly after their birth.

Andres S. Bustamante served as lead for conceptualization, formal analysis, funding acquisition, methodology, writing–original draft, and writing–review and editing and contributed equally to data curation. Vanessa N. Bermudez served as lead for data curation, contributed equally to writing–review and editing, and served in a supporting role for conceptualization, formal analysis, and writing–original draft. Karlena D. Ochoa contributed equally to formal analysis and served in a supporting role for data curation, writing–original draft, and writing–review and editing. Ashlee B. Belgrave served in a supporting role for data curation, formal analysis, writing–original draft, and writing–review and editing. Deborah Lowe Vandell served in a supporting role for conceptualization, funding acquisition, methodology, writing–original draft, and writing–review and editing.
Correspondence concerning this article should be addressed to Andres S. Bustamante, School of Education, University of California, Irvine, 3200 Education Building, Irvine, CA 92697, United States. Email: asbustam@uci.edu

such as Head Start and Early Head Start, as well as state and local programs such as pre-kindergarten programs, have received increased public funding to provide high-quality care for children from low-income families (Parker et al., 2018; Tout et al., 2010). Nationally, about half of infants and toddlers and three-quarters of preschoolers experience regular non-parental childcare (Burchinal et al., 2015). These public investments seem reasonable given economic studies suggesting that expanding access to early education prior to kindergarten entry may well yield positive returns through later adult earnings (Magnuson & Duncan, 2016). Unfortunately, many of these positive conclusions rest on evidence from three classic studies—Perry Preschool, the Abecedarian Program, and the Chicago Child-Parent Centers. The Perry Preschool and Abecedarian Programs which were run by researchers and involved around 120 children. Research using data from the Chicago Longitudinal Study (1985–1986; $n = 1{,}539$) demonstrated that 2 years of involvement in high-quality preschool programs had positive effects on behavioral outcomes in participants' juvenile years; despite the large sample size, this study only involved a single community (Arteaga et al., 2014). Additional research on the long-term impacts of access to high-quality early childcare and education during the first 5 years is needed because of the importance of its policy implications, particularly for children living near or below the poverty line (Burchinal et al., 2015).

Although disparities in school readiness between children from low-income families and their middle- to high-income peers exist across content domains, they are even more pronounced in Science, Technology, Engineering, and Mathematics (STEM), and remain evident later in children's school career (Morgan et al., 2016). This problem in our STEM education system may contribute to the underrepresentation of racially and ethnically diverse populations (disproportionately represented in low-income populations) in STEM fields (Valantine & Collins, 2015) and unfilled STEM jobs, despite STEM representing one of the fastest growing labor markets. Research suggests that children's STEM identities begin to form in the early childhood years (Pantoya et al., 2015) and that early STEM learning is well associated with high-quality pedagogical practices and teacher-child interactions (Bustamante et al., 2018; Fuccillo, 2011). Indeed, when teachers engage in high-quality interactions as characterized by the most common early childhood measures of quality (Pianta et al., 2008), they are often exercising the fundamental skills that comprise STEM learning, such as engaging in the inquiry process, providing high-quality feedback, exploring novel phenomena to develop concepts, and asking open-ended questions to promote critical thinking (Greenfield et al., 2009).

Myriad studies demonstrate that higher caregiving quality in early childhood education is associated with positive school readiness outcomes for children from low-income families upon kindergarten entry (Barnett et al., 2005; Gormley et al., 2008; Weiland & Yoshikawa, 2013). Few studies, however, examine longitudinal effects of early childcare and education (ECE) quality extending into high school (Vandell et al., 2010, 2016, 2020) and even fewer focus specifically on interest, involvement, and performance in high-school STEM. This study examines two key aspects of caregiving quality: caregivers' sensitivity and responsiveness (sensitivity) and their cognitive stimulation (stimulation) in ECE as predictors of later STEM success and school performance. It also considers the potential of caregivers' sensitivity and stimulation in early care to moderate the relations between family income and later STEM success such that early caregiving quality is a stronger predictor of STEM achievement for children from low-income families compared to their higher income peers. Results from this study will constitute valuable contributions to the field by elucidating the value of quality early childcare and education on promoting later STEM school success. Further, if caregivers' sensitivity and stimulation in early care and education settings do indeed relate to later STEM success, it may be the case that an increased focus on STEM in early childhood education (a content area that is largely ignored in the early years; Greenfield et al., 2017) could promote expanded interest in STEM careers and have implications for increasing representation of low-income populations in STEM fields.

Conceptual Framework

A cognitive advantage hypothesis suggests that high caregiving quality in ECE can provide children from under-resourced environments with a stronger cognitive foundation during early childhood through high levels of language stimulation, access to developmentally appropriate learning materials, a positive emotional climate with responsive caregiving, and opportunities for children to safely explore their environment (National Institute of Child Health and Human Development Early Child Care Research Network, 2000). Evidence from ECE interventions supports this hypothesis as children from low-income families who attend ECE with higher caregiving quality displaying increased math and language achievement throughout their academic careers as well as higher wages in adulthood (Campbell et al., 2002; Schweinhart et al., 2005).

Research and theory also suggest that high-quality early care practices support a strong foundation for science learning. High-quality interactions are often characterized by contingent back-and-forth interactions between caregivers and children, especially those that pose open-ended questions and allow children to think critically and solve problems (Hirsh-Pasek et al., 2015). Science is a process of explaining the natural world through systematic inquiry and exploration. Chouinard (2007) explains the role that children's questions play in their cognitive development when they encounter a gap in their current knowledge. Children are particularly receptive to new information when it is borne of their own curiosity, and which can have depth of processing benefits (Chouinard, 2007). By engaging in these inquiry processes at a young age, children may feel more comfortable and confident during STEM learning opportunities when they encounter them in school. While there is evidence for this kind of skill-building hypothesis for math and language outcomes (Burchinal et al., 2000; McCartney et al., 2007), little research has examined these kinds of long-term benefits of early education for the science, technology, and engineering portions of STEM learning.

Longitudinal Associations of Early Care and Education

Several studies have examined the long-term benefits of access to high-quality early childcare and education in the Study of Early Child Care and Youth Development (SECCYD), the large multi-site national study that we used in this study. Vandell et al. (2016) examined the longitudinal relations between early childcare and academic outcomes at the end of high school using the SECCYD data set. They report that center-based care and higher quality childcare from ages 6 to 54 months were associated with increased class rank and grades, respectively.

Other studies have examined the specific benefits of quality early care for children from low-income families in the SECCYD data set in which about 25% of the sample was from low-income backgrounds. McCartney et al. (2007) explored whether childcare quality might be particularly important for children from low-income families and if it may also improve children's home environment. They found an interaction between family income and childcare quality that predicted children's language ability upon school entry as well as improvements in the home environment; suggesting that quality care is particularly valuable to children from low-income backgrounds and benefits can extend beyond the classroom into the home.

In a related study, Dearing et al. (2009) tested a similar interaction between childcare quality and family income predicting math and reading achievement in Grades 3 through 5 (ages 8–11 years). They found a moderation effect in which lower family income was less strongly associated with underachievement in third to fifth grade for children who experienced higher quality care from during early childhood (ages 6–54 months). They also found that higher quality care was associated with math and reading achievement indirectly through increased school readiness skills at kindergarten entry, consistent with a mediation effect. The studies cited above have examined ECE quality across the first 5 years predicting age 15 academic outcomes without a specific emphasis on low-income families; they have also examined interactions of early care quality with family income predicting early childhood math and reading outcomes as well as these outcomes in Grades 3 through 5. What has yet to be examined are the associations with ECE caregiver sensitivity and stimulation quality for children from low-income families with age 15 outcomes, and specifically with STEM school performance and achievement.

This is a meaningful gap in the literature as high-quality teacher/caregiver practices demonstrate strong overlap with best practices in STEM learning. For example, Kook and Greenfield (2021) used the Classroom Assessment Scoring System (CLASS; Pianta et al., 2008) to observe Head Start preschool classrooms during language and literacy, social-emotional, and STEM-focused activities. They found that teacher's emotional support and classroom organization were consistent across settings, however, they reported significantly higher scores on the instructional support domain of the CLASS (concept development, quality of feedback, and advanced language modeling) during STEM activities. This suggests that these high-quality instructional practices are naturally elicited during STEM activities and teachers who are engaging children in these practices may be helping children build a strong foundation for later STEM learning. This study will test this hypothesis by examining whether two specific aspects of caregiving quality in ECE experiences—sensitivity and responsiveness and cognitive stimulation—predict STEM achievement and STEM school performance in third through fifth grade and high school and whether these relationships are stronger for children from low-income backgrounds.

Research Questions and Hypotheses

Research Question 1: Do caregiving sensitivity and stimulation between ages 6 and 54 months and children's family income predict STEM achievement at age 15 controlling for a host of child- and family-level covariates?

Hypothesis 1: Sensitivity and stimulation in ECE between 6 and 54 months will be associated with higher STEM achievement at age 15 and lower family income will be associated with lower STEM achievement at age 15. We also hypothesized that cognitive stimulation would have a uniquely predictive relationship with STEM achievement.

Research Question 2: Do caregiving sensitivity and stimulation between ages 6 and 54 months moderate the relationship between family income and age 15 STEM achievement such that early quality is a stronger predictor of STEM achievement for children from low-income families compared to their higher income peers?

Hypothesis 2: Sensitivity and stimulation in ECE will moderate relations between family income and age 15 STEM achievement by serving as a unique predictor of STEM achievement for children from low-income families.

Research Question 3: Does STEM performance in Grades 3 through 5 indirectly affect the relationship between caregiving sensitivity and stimulation between ages 6 and 54 months and age 15 STEM achievement among children from low-income families?

Hypothesis 3: STEM achievement in Grades 3 through 5 will serve as an indirect effect between the relationship between sensitivity and stimulation in early care and education and age 15 STEM achievement, consistent with a cognitive advantage hypothesis.

Method

Sample and Study Design

Data were drawn from the National Institute of Child Health and Human Development (NICHD) Study of Early Child Care and Youth Development (SECCYD; NICHD Early Child Care Research Network & Duncan, 2003). The publicly available portion of the dataset follows 1,364 families from their child's birth in 1991 until age 15 with four major phases of data collection across the entire 15-year study, including data collection time points at 1, 6, 15, 24, 36, and 54 months, as well as in Grades K, 1, 3, 4, 5, and 9. The sample included economically, and geographically diverse families recruited from hospitals surrounding cities within the United States (Little Rock, AR; Irvine, CA; Lawrence, KS; Boston, MA; Philadelphia, PA; Pittsburgh, PA; Charlottesville, VA; Seattle, WA; Morganton, NC; and Madison, WI). From the initial sample of 1,364 families, 979 remained in the study through age 15. The sample for the current study consisted of 1,096 participants with non-missing information about the site of data collection because in our analyses we clustered standard errors by site.

Measures

See Table 1 for descriptive statistics for the study variables and covariates for the original SECCYD sample of 1,364 families and the 1,096 families in the analysis sample.

Family Income-to-Needs Ratio

Mothers reported annual household income from all sources at the 6-, 15-, 24-, 36-, and 54-month assessments. For each time point, the

Table 1
Descriptive Statistics for the Recruitment and Analysis Samples

Variable	Original sample (*N* = 1,364)			Analysis sample (*N* = 1,096)			Likelihood of retained	
	n	*M*	*SD*	*n*	*M*	*SD*	*t*	*p*
Family income-to-needs	1,302	3.6	2.85	1,094	3.82	2.91	6.47	<.001
At poverty level or below		11.14%			8.23%			
Low income		19.05%			18.28%			
Low to middle income		21.97%			21.66%			
Middle income		15.67%			16.27%			
High income		32.18%			35.56%			
ECE quality of care[a]								
Episodes in higher caregiver cognitive stimulation	1,364	0.29	0.61	1,096	0.44	0.73	8.87	<.001
Episodes in higher caregiver sensitivity/responsiveness	1,364	1.11	1.20	1,096	1.36	1.21	17.27	<.001
STEM achievement age 15								
Applied problems	887	102.92	14.2	789	102.91	14.10		
STEM school performance age 15								
Most advanced science course	730			654				
No science course taken		8.36%			8.41%			
Survey science		30.82%			30.43%			
Earth science		20.68%			20.34%			
Biology		33.70%			34.25%			
Chemistry		0.82%			0.76%			
Physics		5.34%			5.50%			
Advanced science		0.27%			0.31%			
Most advanced math course	730			654				
No math course taken		5.21%			4.74%			
Below Algebra I		4.25%			4.59%			
Algebra I		51.37%			51.22%			
Geometry		30.82%			31.04%			
Algebra II		7.95%			8.10%			
Advanced math		0.41%			0.31%			
Calculus		0.00%			0.00%			
GPA in science courses	667	2.91	0.93	597	2.92	0.92		
GPA in math courses	690	2.85	0.93	621	2.86	0.92		
STEM achievement Grades 3–5								
Applied problems Grade 3	1,013	115.05	15.00	903	115.51	14.7		
Broad math Grade 3	1,012	116.26	17.3	902	116.73	16.9		
Calculations Grade 3	1,010	115.81	18.7	901	116.08	18.60		
Applied problems Grade 5	993	109.31	13.5	887	109.57	13.3		
Broad math Grade 5	993	110.66	17.4	887	110.91	17.00		
Calculations Grade 5	991	108.66	16.5	885	108.84	16.1		
Block design and matrix reasoning Grade 4	1,015	104.37	14.6	906	104.58	14.7		
Child covariates								
Gender = female	1,364	48.31%		1,096	48.63%		0.47	.64
Race	1,364			1,096				
European American		80.43%			82.21%		3.37	<.001
African American		12.90%			11.31%		−3.55	<.001
Asian American		1.61%			1.55%		−0.37	.71
Native American		0.37%			0.36%		−0.02	.98
Other		4.69%			4.56%		−0.46	.65
Negative mood—6 months	593	1.69	0.49	555	1.69	0.49	−0.65	.52
Positive mood—6 months	593	2.36	0.52	555	2.37	0.52	1.18	.24
Health—6 months	1,279	3.34	0.74	1,079	3.34	0.72	0.88	.38
Early cognitive ability—15 months	1,180	108.58	14.1	1,036	108.69	14.1	0.76	.45
Maternal covariates								
Race	1,364			1,096				
European American		82.62%			84.31%		3.33	<.001
African American		12.76%			11.13%		−3.65	<.001
Asian American		2.20%			2.19%		−0.05	.96
Native American		0.59%			0.64%		0.51	.61
Other		1.83%			1.73%		−0.55	.58
Marital status	1,197			1,048				
Married, living together		77.86%			78.34%		1.06	.29
Partnered, living together		8.35%			8.49%		0.46	.65
Separated, not living together		3.51%			3.91%		2.01	.04
Divorced, not living together		0.33%			0.38%		0.75	.45
Widowed		0.08%			0.10%		0.38	.71
Never married, not living together		9.86%			8.78%		−3.33	<.001

(*table continues*)

Table 1 (*continued*)

Variable	Original sample ($N = 1{,}364$)			Analysis sample ($N = 1{,}096$)			Likelihood of retained	
	n	*M*	*SD*	*n*	*M*	*SD*	*t*	*p*
Age	1,364	28.11	5.63	1,096	28.45	5.53	4.49	<.001
Years of education	1,363	14.23	2.51	1,096	14.44	2.45	6.32	<.001
Traditional beliefs for raising kids	1,360	60.34	15.2	1,095	59.37	14.80	−4.79	<.001
Sensitivity—6 months	1,272	9.21	1.78	1,073	9.26	1.76	2.32	.02
Vocabulary—36 months	1,167	99.01	18.4	1,033	99.84	18.2	4.33	<.001
HOME at 15 months	1,234	37.31	4.68	1,074	37.48	4.58	3.36	<.001

Note. ECE = early care and education; STEM = science, technology, engineering, and mathematics; GPA = grade point average; HOME = Home Observation Measure of the Environment.
[a] Across the five time points at which ECE quality of care was observed in the analysis sample, 20.6% of children had data for only one observation, 18.0% had data for two observations, 15.6% had data for three observations, 18.4% had data for four observations, and 27.4% had data for all five observations.

income-to-needs ratio was calculated by dividing the family income by the poverty threshold based on family size, as established by the U.S. Census Bureau. For our analysis, we computed an average family income-to-needs ratio for children's early childhood from 6 to 54 months of age. A ratio of 1 is the poverty line, 2 or below is low-income, 3 is middle-income, and 4 or above is high-income; in our sample, the average income-to-needs-ratio was 3.82 ($SD = 2.91$; Bustamante et al., 2022; Dearing et al., 2009). The sample consisted of 8.23% families at poverty level or below, 18.28% low-income families, 21.66% low- to middle-income families, and 51.83% middle- and high-income families. For the original SECCYD sample, the average income-to-needs-ratio was 3.60 ($SD = 2.85$) with 11.14% and 19.05% of families having an income level at poverty level or below or low income, respectively, and 47.85% middle and high income.

Early Care and Education Caregiving Quality

To capture early caregiving and education quality, *caregiver cognitive stimulation* was observed and rated at ages 6, 15, 24, 36, and 54 months, as was caregiver sensitivity and responsiveness using the Observational Record of the Caregiving Environment (ORCE), a live observational instrument designed for the SECCYD (Bustamante et al., 2022; National Institute of Child Health and Human Development Early Child Care Research Network, 2000). Observations were conducted for all study children who received 10 hr or more of non-parental care each week in either center-based care, child-care homes (family daycare), or in-home care by a relative or nonrelative during half-day visits consisting of several 44-min observation cycles. At ages 6, 15, 24, and 36 months, two half-day visits were conducted while only one-half-day visit was conducted at 54 months. Observers rated caregiver's sensitivity to children's expressions of non-distress and stimulation of cognitive development using 4-point scales (1 = *not at all characteristic*, 2 = *somewhat not characteristic*, 3 = *characteristic*, and 4 = *highly characteristic*). The validity of the ORCE has been documented in a variety of studies demonstrating associations with later academic achievement, behavioral outcomes, college graduation, and salary in adulthood (Bustamante et al., 2022; Duncan et al., 2019; Vandell et al., 2016).

For each time point, we assessed whether the child was in higher process quality care (score of 3 or above on the ORCE for each variable). In line with the approach taken by Dearing et al. (2009), rating below 3, or missing, were coded as 0, or not being in high process quality in that dimension. Caregiver cognitive stimulation and caregiver sensitivity/responsiveness in our model was represented by the total number of timepoints (0–5) received a higher process quality score on that quality dimension. The mean for number of time points in higher quality care for caregiver cognitive stimulation was 0.44 ($SD = 0.73$) and caregiver sensitivity/responsiveness was 1.36 ($SD = 1.21$).

For the interaction terms between family income-to-needs ratio and the two ECE quality measures (e.g., ages where the child received high-quality care for cognitive stimulation, and ages where the child received high-quality sensitivity/responsiveness), we centered the income-to-needs ratio at the sample mean and used it as a continuous variable. This approach is in line with previous studies examining income as a moderator of the relationship between early quality and later academic achievement in the SECCYD dataset (Dearing et al., 2009).

STEM Achievement and School Performance at Age 15

For STEM Achievement, we used students' standardized score in the Applied Problems subscale of the Woodcock–Johnson test which examines people's ability to solve mathematics problems. The average standardized score for students in the sample was 102.91 ($SD = 14.10$), which was similar to that of the original sample ($M = 102.92$, $SD = 14.22$). For STEM school performance, we used students' most advanced science course completed, the most advanced math course completed, grade point average (GPA) in science courses, and GPA in math courses. Science courses were coded numerically in the following manner: 0 = *no science course taken*, 1 = *survey science*, 2 = *earth science*, 3 = *biology*, 4 = *chemistry*, 5 = *physics*, and 6 = *advanced science*. Math courses were coded numerically in the following manner: 0 = *no math course taken*, 1 = *below algebra I*, 2 = *algebra I*, 3 = *geometry*, 4 = *algebra II*, 5 = *advanced mathematics*, and 6 = *calculus*. The NICHD SECCYD team used the science and math course codes by the Classification of Secondary School Courses (Perkins et al., 2004) to align the courses of participants in the study to ninth-grade national-level sequence of science and math courses. Table 1 shows the percentage of students for most advanced science and math courses for the analysis and original samples. GPA information was extracted from student transcripts by school personnel and ranged from 0 to 4. To calculate STEM school performance at age 15, we *z*-scored each of the four variables and then averaged across the z-scores to get a composite score.

Third Through Fifth Grade STEM Achievement

STEM achievement during third, fourth, and fifth grade consisted of the Applied Problems, Broad Math, and Calculations subtests of the Woodcock–Johnson in Grades 3 and 5, as well as the Block Design and Matrix Reasoning Task from the Wechsler Abbreviated Scale of Intelligence (WASI) in Grade 4. The Woodcock–Johnson Applied Problems subtest assesses an individual's ability to solve problems, the calculation subtest assesses an individual's calculation skills (e.g., addition, subtraction, multiplication, and division), and broad math is a cluster of calculation, math fluency, and applied problems. WASI provides an estimate of general cognitive abilities of individuals ages 6–89 producing measures of intelligence and verbal and non-verbal skills. The Block Design activity assesses individuals' ability to replicate abstract designs using blocks and the Matrix Reasoning Task observes individuals' visual organizational skills and nonverbal reasoning. Table 1 shows similar mean and standard deviation values between the analysis and original samples across all the variables recorded when students were in third through fifth grade. To calculate STEM achievement in third through fifth grade, we z-scored each of the seven measures and then averaged across the z-scores to get a composite score.

Covariates

For study covariates, we used an extensive array of child, maternal, and household characteristics between ages 6- and 24-months that have been shown to associate with selection into higher quality child care in previous research (Dearing et al., 2009). For child covariates, we used gender ($0 = male$, $1 = female$), race/ethnicity, behavioral adjustment and health, and cognitive skills (see Table 1). Approximately 48% of children in the analysis and original samples were female. About 80% of children were European American, 13% African American, 2% Asian American, less than 1% Native American, and 5% of other race, resembling the race and ethnicity distribution of the original sample. Children's negative and positive moods were assessed from video recordings of mother–child semi-structured interactions of free play at 6 months using 4-point ratings of maternal sensitivity to their child's moods (e.g., to distress, non-distress), intrusiveness (reverse scored), and positive and negative regard. Information regarding children's health, including respiratory and intestinal problems, the mother's overall health rating of her child, number of visits to the doctor, and hospitalizations, was gathered at 6 months via structured interviews with mothers. Early cognitive ability was assessed with the Bayley Scales of Infant Development at 15 months (Bayley, 1969).

Mother's age, race/ethnicity, education, marital status, parenting beliefs, parenting sensitivity, and vocabulary were also used as covariates. Mothers' age, race/ethnicity, and years of education were gathered at intake, in the structured home interviews at 1-month, and mother's marital status at 24 months was also recorded. Mother's traditional beliefs for raising children were collected at the 1-month interview using the Parental Modernity (PM) Scale of Child-rearing and Educational Beliefs Likert questionnaire which measures parents' progressive/democratic and authoritarian beliefs about child-rearing (Schaefer & Egarton, 1985). Maternal sensitivity was evaluated at 6 months using semi-structured mother–child interactions of free play and was rated using the following items on four-point rating scales: sensitivity to non-distress, positive regard, and intrusiveness (reversed scored). Mothers' receptive vocabulary was evaluated using the Peabody Picture Vocabulary Test-Revised during the 36-month assessment (Dunn & Dunn, 1981). Home environment quality at 15 months was evaluated using the Home Observation Measure of the Environment (HOME; Bradley & Caldwell, 1984), an interview and observation measures that assess parental responsiveness, acceptance, and involvement, and environment characteristics such as home organization, the availability of learning materials, and variability of experiences provided to the child. We chose these covariates at the described time-points because they were the earliest time-points during early childhood at which they were available. Although we would have preferred for all the covariates to precede the quality of care measures (e.g., intake or 6-month visit), children's Bayley scores and HOME environment ratings were first collected at the 15 months visit, and mother's vocabulary was only measured at the 36-month.

Attrition

Although the means for the analysis sample and the original sample of 1,364 families were very similar, we examined the potential for differential attrition. First, we conducted bivariate analyses to examine whether family income-to-needs ratio, caregiver cognitive stimulation and sensitivity, and the covariates, one by one, were associated with the likelihood of remaining in the analysis sample (see Table 1). We found small but statistically significant differences in rates of attrition. Specifically, families were more likely to be retained in the study if they had a higher average family income-to-needs ratio from 6 to 54 months of age and the children or mothers were European American, but less likely to be retained if the children or mothers were African American. Furthermore, children were more likely to be retained if they had more episodes of higher caregiver cognitive stimulation and sensitivity/responsiveness, and if their mothers were older, more educated, more sensitive, or scored higher on the vocabulary test. On the contrary, children were less likely to be retained if their mothers had never married or they held lower levels of traditional beliefs for raising kids. Next, we examined family income-to-needs ratio, ECE cognitive stimulation, ECE sensitivity/responsiveness, and the 14 covariates (race and marital status were dummy coded) simultaneously, in a multivariate model. Combined, the variables explained 5.4% of the variance in retention rate.

Data Analysis Plan

This study used a path model approach to allow for estimation of missing data using full information maximum likelihood (FIML). FIML estimates parameters using all the information available. Specifically, it generates an estimated covariance matrix of those that would have been obtained if the missing values were replaced by their most likely values. Using Mplus Version 7.1 (Muthén & Muthen, 2017), we conducted a moderated mediation analyses to answer the research questions testing the following models:

1. Age 15 STEM achievement and STEM school performance were regressed on family income and number of time points (0–5, 6, 15, 24, 36, and 54 months) in higher quality

caregiver cognitive stimulation and higher caregiver sensitivity/responsiveness, controlling for covariates (child gender, race/ethnicity, behavioral adjustment health, and cognitive skills, as well as the mothers' age, race/ethnicity, education, parenting values, parenting sensitivity, vocabulary, and marital status).

2. To test for moderation, an interaction term between family income and time-points in high-quality caregiving stimulation and high-quality caregiving sensitivity (between ages 6 and 54 months) was added to the model to examine if either of these caregiving dimensions moderated the relations between family income and age 15 STEM achievement and STEM school performance.
3. To test for our hypothesized path model, the product of the coefficients comprising the indirect pathways from number of time periods with high caregiving stimulation and high caregiving sensitivity to STEM achievement in Grades 3 through 5 and, in turn from STEM achievement during these years to age 15 STEM achievement and STEM school performance was estimated.

To determine model fit we examined the Bentler comparative fit index (CFI), the standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA). The caregiver cognitive stimulation model (CFI = 0.84, SRMR = 0.09, RMSEA = 0.09) and the caregiver sensitivity and responsiveness model (CFI = 0.84, SRMR = 0.10, RMSEA = 0.09) both revealed adequate model fit. Chi-square can provide unreliable estimates with large sample sizes, therefore we did not use it as a metric of fit (Kline, 2011).

Results

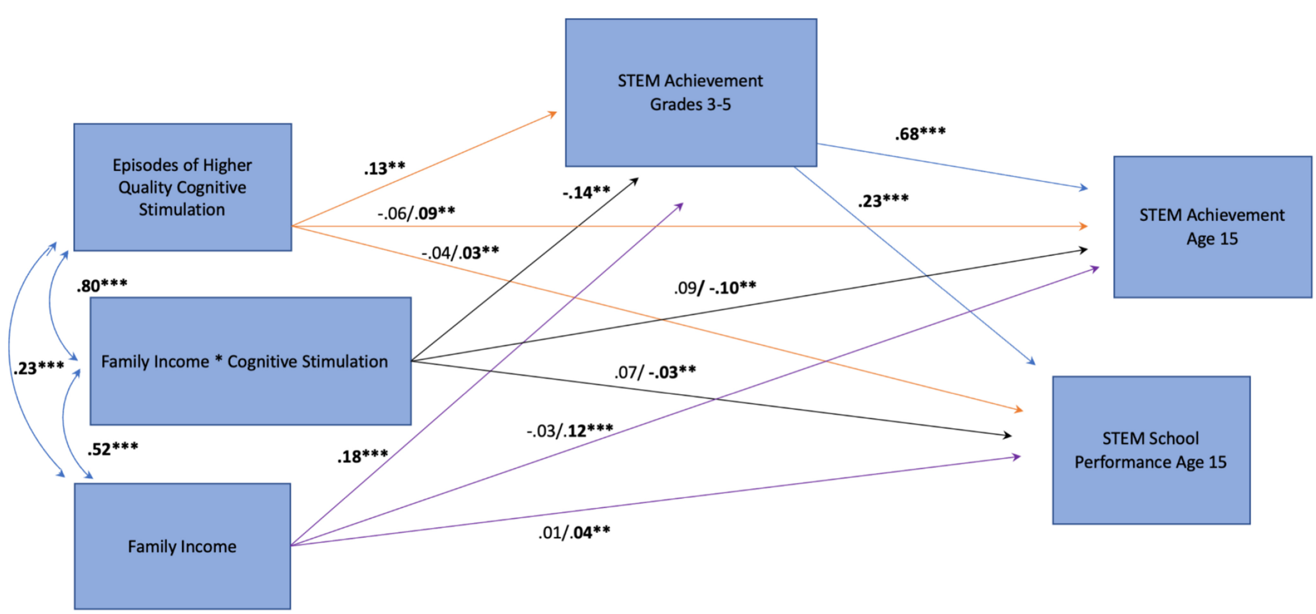
Results of the moderated mediation analyses are presented in Figures 1 and 2. Figure 1 presents a path model of STEM achievement in Grades 3 through 5 serving as an indirect effect on the relationship between an interaction of caregiver cognitive stimulation with family income and STEM achievement at age 15. Figure 2 depicts the same model but with caregiver sensitivity and family income as predictors. Here we present the main results, but all results are presented in Tables 2 and 3.

Caregiver Sensitivity and Responsiveness

First, we present results examining relations between early caregiver sensitivity and responsiveness and family income during early childhood on STEM achievement and school performance at age 15. We did find a significant direct effect of caregiver sensitivity/responsiveness on STEM school performance at age 15 ($\beta = -0.16$, $SE = 0.10$, $p = .01$) but not on STEM achievement ($\beta = -0.06$, $SE = 0.38$, $p = .09$) at age 15. Yet, there was not a significant direct effect of family income on either STEM school

Figure 1

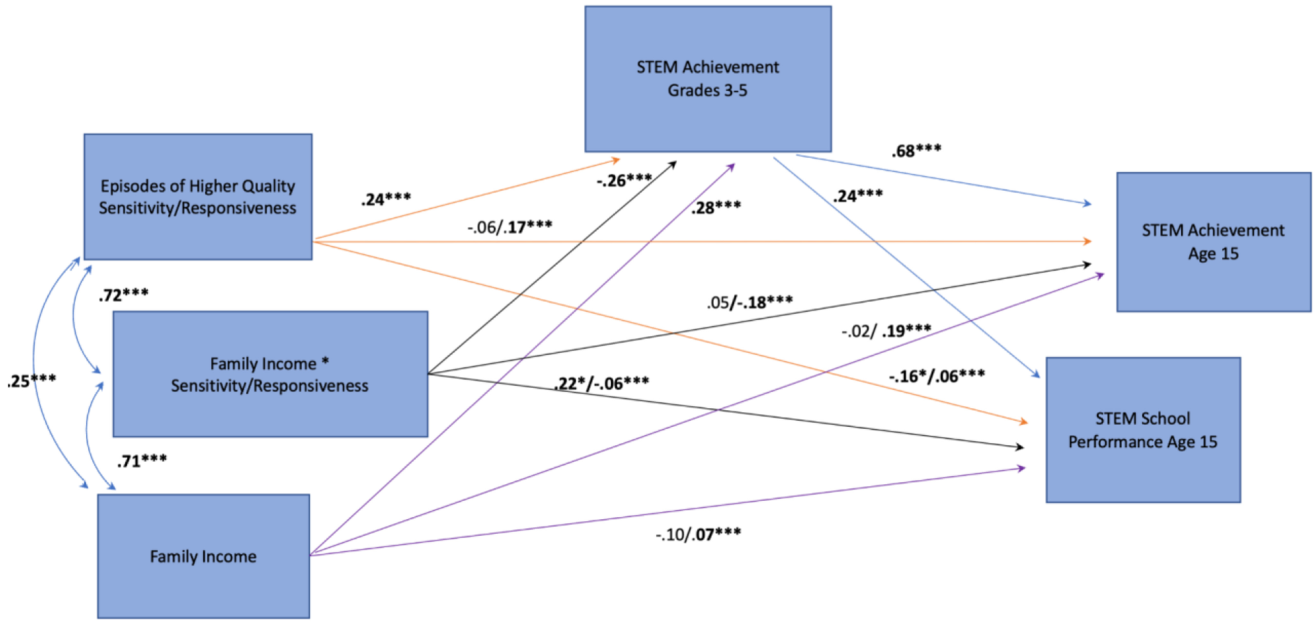
Path Model of the Relationship Between an Interaction of Caregiver Cognitive Stimulation With Family Income and STEM Achievement at Age 15 With STEM Achievement in Grades 3–5 Serving as a Significant Pathway



Note. Child level covariates include child gender, ethnicity, Bayley Mental Development index at age 15 months, positive and negative mood at 6 months, Child Behavior Checklist total problem scores rated by caregiver at 24 months, and health of child at 6 months. Family level covariates include mothers age, ethnicity, maternal sensitivity, maternal education, mothers' vocabulary (PPVT), HOME total score, mothers' traditional beliefs on parenting, and maternal marital status at 24 months. STEM = science, technology, engineering, and mathematics; PPVT = Peabody Picture Vocabulary Test-Revised. See the online article for the color version of this figure.
$^{**} p < .01$. $^{***} p < .001$.

Figure 2

Path Model of the Relationship Between an Interaction of Caregiver Sensitivity and Responsiveness With Family Income and STEM Achievement at Age 15 With STEM Achievement in Grades 3–5 Serving as a Significant Pathway



Note. Child level covariates include child gender, ethnicity, Bayley Mental Development index at age 15 months, positive and negative mood at 6 months, Child Behavior Checklist total problem scores rated by caregiver at 24 months, and health of child at 6 and 24 months. Family level covariates include mothers age, ethnicity, maternal sensitivity, maternal education, mothers' vocabulary (PPVT), HOME total score, mothers' traditional beliefs on parenting, maternal depression at 24 months, and maternal marital status at 24 months. STEM = science, technology, engineering, and mathematics; PPVT = Peabody Picture Vocabulary Test-Revised. See the online article for the color version of this figure.
$^{*}p < .05$. $^{***}p < .001$.

performance at age 15 ($\beta = -0.10$, $SE = 0.04$, $p = .07$), or STEM achievement ($\beta = -0.02$, $SE = 0.29$, $p = .80$).

We then tested the interaction between income and caregiver sensitivity and responsiveness on STEM Achievement and STEM school performance, with STEM achievement in Grades 3–5 as a pathway. Our analyses revealed a significant interaction of family income by cognitive stimulation on STEM school performance at age 15 ($\beta = 0.22$, $SE = 0.02$, $p = .02$) but not on STEM achievement ($\beta = 0.05$, $SE = 0.11$, $p = .47$). Furthermore, there was a significant indirect effect, such that STEM achievement in Grades 3–5 served as a pathway between the interaction term and STEM achievement, ($\beta = -0.18$, $SE = 0.06$, $p < .001$), and STEM school performance, ($\beta = -0.06$, $SE = 0.003$, $p < .001$). Once more, we found that STEM achievement in Grades 3–5 served as a pathway linking caregiving quality and STEM academic achievement and school performance at age 15.

Caregiver Cognitive Stimulation

Next, we turn to our results examining the relations between caregiver cognitive stimulation and family income during early childhood on STEM achievement and STEM school performance at age 15. In addition, we considered whether relations between number of episodes in which caregivers provided cognitively rich stimulation in early caregiving settings and age 15 STEM achievement was indirectly affected by STEM achievement in elementary school, particularly among children from low-income families.

We did not find significant direct effects between early caregiver cognitive stimulation or family income on STEM school performance, ($\beta = -0.04$, $\beta = 0.01$, $ps > .05$) or STEM achievement ($\beta = -0.06$, $\beta = -0.03$, respectively, $ps > .05$) at age 15. Next, we tested the interaction between income and caregiver cognitive stimulation on age 15 STEM achievement and STEM school performance and examined the indirect effect of STEM achievement in Grades 3–5. Our analyses did not reveal a significant interaction of family income by cognitive stimulation on STEM achievement at age 15 ($\beta = 0.09$, $SE = 0.17$, $p = .13$), or STEM school performance ($\beta = 0.07$, $SE = 0.02$, $p = .30$). Yet we did find a significant indirect effect in which the interaction of income and caregiver cognitive stimulation predicts STEM achievement in Grades 3–5 which in turn predicts STEM achievement at age 15 ($\beta = -0.10$, $SE = 0.09$, $p = .003$) and STEM school performance at age 15 ($\beta = -0.03$, $SE = 0.01$, $p = .004$). Taken together, these results suggest that higher quality cognitive stimulation was a stronger predictor of high school STEM achievement and school performance for children from low-income families compared to their higher income peers.

Discussion

The United States STEM education and career pipelines are sorely lacking (Hinton et al., 2020; Ketenci et al., 2020). This is particularly

Table 2

Moderated Mediation Analysis for Income and Caregiver Cognitive Stimulation Moderating STEM Achievement in Grades 3–5 on Age 15 STEM School Performance and Achievement

DV: Age 15 STEM school performance				
	Dependent variable model			
Predictor	*B*	*SE*	*t*	*p*
CogStim	−0.04	0.14	−0.81	.42
Income	0.01	0.04	0.19	.85
Income × CogStim	0.07	0.02	1.04	.30
STEM achievement in Grades 3–5	0.23	0.08	6.83	<.001
	Indirect effect model (STEM achievement in Grades 3–5)			
Predictor	*B*	*SE*	*t*	*p*
CogStim	0.03	0.03	2.65	.008
Income	0.04	0.01	3.17	.002
Income × CogStim	−0.03	0.01	−2.87	.004
DV: Age 15 STEM achievement				
	Dependent variable model			
Predictor	*B*	*SE*	*t*	*p*
CogStim	−0.06	0.95	−1.21	.23
Income	−0.03	0.19	−0.84	.40
Income × CogStim	0.09	0.17	1.51	.13
STEM achievement in Grades 3–5	0.68	0.51	22.25	<.001
	Indirect effect model (STEM achievement in Grades 3–5)			
Predictor	*B*	*SE*	*t*	*p*
CogStim	0.09	0.66	2.63	.009
Income	0.12	0.14	4.22	<.001
Income × CogStim	−0.10	0.09	−2.96	.003

Note. The betas are standardized coefficients. DV = dependent variable; STEM = science, technology, engineering, and mathematics; CogStim = number of episodes in higher caregiver cognitive stimulation; Income = family income-to-needs ratio.

true for individuals from underserved and low-income communities. Even with growing efforts to improve STEM education and diversify the STEM workforce, individuals from underserved and low-income communities continue to be underrepresented in STEM careers compared to higher-income peers. This is an issue because STEM careers are often high-paying and prestigious (Xu, 2013). Further, science itself suffers when there is a lack of diversity as new perspectives bring new ideas which drive innovation. Prior research has demonstrated that higher caregiving quality during early childhood promotes children's math and reading achievement in middle childhood, particularly for children from low-income communities (Dearing et al., 2009). The current study examined two specific aspects of caregiving quality in ECE settings during early childhood—high caregiver sensitivity and high caregiver cognitive stimulation—in relation to STEM achievement and school performance in high school, asking if low-income children derived greater benefit from these aspects of positive caregiving.

Results suggest that caregiving quality in ECE can build a strong foundation for a trajectory of STEM success. We found that two aspects of caregiving quality (cognitive stimulation and sensitivity-responsivity) predicted STEM achievement in late elementary school (third, fourth, and fifth grade) which in turn predicted STEM achievement and school performance in high school (age 15). This included a significant indirect effect from caregiving quality in ECE to high school STEM suggesting a skills pathway while children were in third, fourth, and fifth grade, linking caregiving quality in ECE and high school STEM achievement. Further, there was a significant interaction between family income and caregiver sensitivity, such that more exposure to sensitive and responsive caregiving in ECE was a stronger predictor of high school STEM school performance for children from low-income families compared to their higher income peers. Together, these results highlight caregiver cognitive stimulation and sensitivity and responsiveness in ECE as an area for investment to strengthen the STEM pipeline, and this might be a particularly impactful approach for children from low-income households.

Our results contribute to the evidence base for positive long-term associations between caregiving quality in ECE and later STEM achievement and school performance with a sample of community-based ECE that is more reflective of common modern ECE settings than experimental studies from the 1960s and 1970s. Classic

Table 3

Moderated Mediation Analysis for Income and Caregiver Sensitivity and Responsiveness Moderating STEM Achievement in Grades 3–5 on Age 15 STEM School Performance and Achievement

DV: Age 15 STEM school performance				
	Dependent variable model			
Predictor	*B*	*SE*	*t*	*p*
Sens	−0.16	0.10	−2.57	.01
Income	−0.10	0.04	−1.83	.07
Income × Sens	0.22	0.02	2.37	.02
STEM achievement in Grades 3–5	0.24	0.07	7.55	<.001
	Indirect effect model (STEM achievement in Grades 3–5)			
Predictor	*B*	*SE*	*t*	*p*
Sens	0.06	0.02	4.20	<.001
Income	0.07	0.01	3.64	.07
Income × Sens	−0.06	0.003	−4.40	<.001
DV: Age 15 STEM achievement				
	Dependent variable model			
Predictor	*B*	*SE*	*t*	*p*
Sens	−0.06	0.38	−1.72	.09
Income	−0.02	0.29	−0.26	.80
Income × Sens	0.05	0.11	0.72	.47
STEM achievement in Grades 3–5	0.68	0.52	22.01	<.001
	Indirect effect model (STEM achievement in Grades 3–5)			
Predictor	*B*	*SE*	*t*	*p*
Sens	0.17	0.35	5.50	<.001
Income	0.19	0.20	4.62	<.001
Income × Sens	−0.18	0.06	−4.71	<.001

Note. The betas are standardized coefficients. DV = dependent variable; STEM = science, technology, engineering, and mathematics; Sens = number of episodes in higher caregiver sensitivity/responsiveness = ; Income = family income-to-needs ratio.

experimental studies, such as the Perry, Abecedarian, and Chicago Child-Parent Centers intervention studies (Arteaga et al., 2014, Campbell et al., 2002; Schweinhart et al., 2005), examined long-term impacts of ECE with impressive results lasting into adulthood. However, these were relatively small and highly resourced studies that would be difficult to replicate at scale. The current study offers ecological validity by examining caregiving quality in ECE in community-based settings at 10 geographically and economically diverse sites. Also notable is that we examined caregiving quality in ECE across the first 5 years of children's lives, and not just a single, pre-kindergarten year. Our results are consistent with the classic experimental studies like the Abecardian study that demonstrated long-term impacts of ECE and provided high-quality care across the first 5 years (Campbell et al., 2002; Schweinhart et al., 2005).

This study also investigated two aspects of caregiving quality in ECE to test if cognitive stimulation and caregiver sensitivity-responsiveness were differentially linked to specific outcomes. We hypothesized that cognitive stimulation might be uniquely predictive of later STEM achievement. This hypothesis was grounded in evidence that science activities in Head Start classrooms fostered higher scores in the instructional support domain of the CLASS (quality of feedback, concept development, and language modeling; Pianta et al., 2008) compared to other content domains, but did not differ in the other domains of emotional support or classroom organization (Kook & Greenfield, 2021). The idea is that science exploration naturally elicits open-ended questions, back-and-forth exchanges, deep exploration of concepts, and rich vocabulary which are all indicators of instructional support. Therefore, we expected that ECE with high cognitive stimulation might create a strong foundation for STEM learning that would relate to later STEM success. Our findings did not support this hypothesis. Instead, we found that both indicators of caregiving quality (cognitive stimulation and caregiver sensitivity and responsiveness) were associated with later STEM school performance and achievement through STEM achievement in third to fifth grade.

Few studies examining the influence of caregiving quality in ECE on later outcomes have asked whether ECE may benefit children differentially depending on their family income. Because the SECCYD data set included a range of family income, this study was able to test for an interaction where caregiving quality ECE might be more meaningful for children from low-income families, and indeed this is what we found. This aligns with previous research using the SECCYD dataset which found that family income moderated the relationship between episodes in high-quality ECE and academic achievement in Grades 3–5, meaning the number of high-quality episodes in ECE was more predictive of positive academic achievement in elementary school for children from low-income household compared to their high-income peers (Dearing et al., 2009; McCartney et al., 2007). Bustamante et al. (2022) demonstrated that these findings extend into adulthood; high-quality ECE erased the disparity between children from low- and higher-income families in their salary and likelihood to graduate from college at age 26. Taken together, these findings have implications for how we invest in ECE, and suggest that when resources are limited, we should prioritize families with the most need.

Finally, we find that relations between caregiving quality in ECE and high school STEM outcomes operated through STEM achievement in third to fifth grade. This lends support for the skills begets skills or skill building hypothesis (Burchinal et al., 2000; Cunha et al., 2006; McCartney et al., 2007) that suggests building an early foundation allows for success in the elementary school context which in turn allows for success beyond that. This finding is also consistent with Dearing et al. (2009) who showed that relations between high-quality ECE and achievement in late elementary school operated through school readiness in kindergarten.

Results from the current study suggest that high-quality caregiver-child interactions in ECE may be a key mechanism for building a foundation for STEM learning. High-quality instructional practices like creating a warm and responsive environment, and stimulating children with back-and-forth exchanges, high-quality feedback, and rich vocabulary prepare students for exploration and inquiry. Building this strong foundation for STEM learning early could have implications for bolstering the STEM workforce and supporting children from low-income families in pursuing high-paying careers and breaking cycles of generational poverty.

Limitations

Several limitations of this study should be noted. First, these data are non-experimental, meaning families were not randomly assigned to different caregiving experiences. This introduces the possibility that selection and omitted variable bias may account for the findings. Families whose children attended ECE with higher caregiver sensitivity and responsiveness may be different from other families and these other differences may account for STEM achievement and school performance at age 15. To address this limitation, we included a rich set of covariates in our analyses. However, experimental evaluations of these phenomena are important for future directions in order to draw causal conclusions. A second limitation is that data collection for this study began in the 1990s and therefore the ECE landscape may have changed since then. However, in order to examine long-term impacts of caregiving quality in ECE it is necessary to utilize longitudinal data. Further, with increased focus on ECE and advancements in research it is likely that caregiving quality in ECE is higher now than it was in the 1990s. Given what we know about the importance of high caregiver stimulation and sensitivity the long-term impacts of ECE might be even greater with modern higher quality care. Another common issue with longitudinal data is attrition, in this dataset, there was differential attrition based on several demographic characteristics including family income and race. We controlled for all variables that showed differential attrition and used full information maximum likelihood which helps reduce bias associated with missing data by using all data to provide the most likely model estimates, although it does not completely eliminate the bias (Duncan et al., 2019). Finally, another issue with using longitudinal data is that the demographics of our country have changed substantially since the 1990s and therefore this sample is not demographically representative of our country today (e.g., Latine families are underrepresented in this sample). Future research is needed to replicate these findings with diverse samples that more accurately reflect the current demographics of the United States.

Conclusion

Caregiver sensitivity and stimulation in ECE during the first 5 years might be key levers for promoting STEM achievement and school performance throughout children's educational careers, especially for children from low-income backgrounds. We should continue to invest early and strategically in education to cultivate the next generation of scientists and innovators who will lead our country.

References

Arteaga, I., Humpage, S., Reynolds, A. J., & Temple, J. A. (2014). One year of preschool or two: Is it important for adult outcomes? *Economics of Education Review*, *40*, 221–237. https://doi.org/10.1016/j.econedurev.2013.07.009

Barnett, W. S., Lamy, C., & Jung, K. (2005). *The effects of state prekindergarten programs on young children's school readiness in five states*. National Institute for Early Education Research.

Bayley, N. (1969). *Manual for the Bayley scales of infant development*. Psychological Corporation.

Bradley, R. H., & Caldwell, B. M. (1984). The HOME Inventory and family demographics. *Developmental Psychology*, *20*(2), 315–320. https://doi.org/10.1037/0012-1649.20.2.315

Burchinal, M., Magnuson, K., Powell, D., & Hong, S. (2015). Early childcare and education. In R. M. Lerner, M. Bornstein, & T. Leventhal (Eds.), *Handbook of child psychology and developmental science: Vol. 4. Ecological settings and processes* (7th ed., pp. 223–267). Wiley. https://doi.org/10.1002/9781118963418.childpsy406

Burchinal, M. R., Peisner-Feinberg, E., Bryant, D. M., & Clifford, R. (2000). Children's social and cognitive development and child care quality: Testing for differential associations related to poverty, gender, or ethnicity. *Applied Developmental Science*, *4*(3), 149–165. https://doi.org/10.1207/S1532480XADS0403_4

Bustamante, A. S., Dearing, E., Zachrisson, H. D., & Vandell, D. L. (2022). Adult outcomes of sustained high-quality early child care and education: Do they vary by family income? *Child Development*, *93*(2), 502–523. https://doi.org/10.1111/cdev.13696

Bustamante, A. S., Greenfield, D., & Nayfeld, I. (2018). Early childhood science and engineering: Engaging platforms for fostering domain-general learning skills. *Education Sciences*, *8*(3), Article 144. https://doi.org/10.3390/educsci8030144

Campbell, F. A., Ramey, C. T., Pungello, E. P., Sparling, J., & Miller-Johnson, S. (2002). Early childhood education: Young adult outcomes from the Abecedarian Project. *Applied Developmental Science*, *6*(1), 42–57. https://doi.org/10.1207/S1532480XADS0601_05

Chouinard, M. M. (2007). Children's questions: A mechanism for cognitive development: IV. Children's questions about animals. *Monographs of the Society for Research in Child Development*, *72*(1), vii–ix. https://doi.org/10.1111/j.1540-5834.2007.00412.x

Cunha, F., Heckman, J. J., Lochner, L., & Masterov, D. V. (2006). Interpreting the evidence on life cycle skill formation. In E. A. Hanushek, & F. Welch (Eds.), *Handbook of the economics of education* (Vol. 1, pp. 698–805). University of Chicago Press.

Dearing, E., McCartney, K., & Taylor, B. A. (2009). Does higher quality early child care promote low-income children's math and reading achievement in middle childhood? *Child Development*, *80*(5), 1329–1349. https://doi.org/10.1111/j.1467-8624.2009.01336.x

Duncan, R. J., Schmitt, S. A., & Vandell, D. L. (2019). Additive and synergistic relations of early mother–child and caregiver–child interactions for predicting later achievement. *Developmental Psychology*, *55*(12), 2522–2533. https://doi.org/10.1037/dev0000824

Dunn, L. M., & Dunn, L. M. (1981). *Peabody picture vocabulary test-revised*. American Guidance Service.

Fuccillo, J. M. (2011). *Higher-level instructional interaction in head start classrooms: Variation across teacher-directed activities and associations with school readiness outcomes* (Doctoral dissertation). University of Miami, Coral Gables, FL.

Gormley, W. T., Phillips, D., & Gayer, T. (2008). The early years. Preschool programs can boost school readiness. *Science*, *320*(5884), 1723–1724. https://doi.org/10.1126/science.1156019

Greenfield, D. B., Alexander, A., & Frechette, E. (2017). Unleashing the power of science in early childhood: A foundation for high-quality interactions and learning. *Zero to Three*, *37*(5), 13–21.

Greenfield, D. B., Jirout, J., Dominguez, X., Greenberg, A., Maier, M., & Fuccillo, J. (2009). Science in the preschool classroom: A programmatic research agenda to improve science readiness. *Early Education and Development*, *20*(2), 238–264. https://doi.org/10.1080/10409280802595441

Hinton, A. O., Termini, C. M., Spencer, E. C., Rutaganira, F. U. N., Chery, D., Roby, R., Vue, Z., Pack, A. D., Brady, L. J., Garza-Lopez, E., Marshall, A. G., Lewis, S. C., Shuler, H. D., Taylor, B. L., McReynolds, M. R., & Palavicino-Maggio, C. B. (2020). Patching the leaks: Revitalizing and reimagining the STEM pipeline. *Cell*, *183*(3), 568–575. https://doi.org/10.1016/j.cell.2020.09.029

Hirsh-Pasek, K., Adamson, L. B., Bakeman, R., Owen, M. T., Golinkoff , R. M., Pace, A., Yust, P. K. S., & Suma, K. (2015). The contribution of early communication quality to low-income children's language success. *Psychological Science*, *26*(7), 1071–1083. https://doi.org/10.1177/0956797615581493

Ketenci, T., Leroux, A., & Renken, M. (2020). Beyond student factors: A study of the impact on STEM career attainment. *Journal for STEM Education Research*, *3*(3), 368–386. https://doi.org/10.1007/s41979-020-00037-9

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.

Kook, J. F., & Greenfield, D. B. (2021). Examining variation in the quality of instructional interaction across teacher-directed activities in head start classrooms. *Journal of Early Childhood Research*, *19*(2), 128–144. https://doi.org/10.1177/1476718X20942956

Magnuson, K., & Duncan, G. J. (2016). Can early childhood interventions decrease inequality of economic opportunity? *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *2*(2), 123–141. https://doi.org/10.7758/rsf.2016.2.2.05

McCartney, K., Dearing, E., Taylor, B. A., & Bub, K. L. (2007). Quality child care supports the achievement of low-income children: Direct and indirect effects through caregiving and the home environment. *Journal of Applied Developmental Psychology*, *28*(5–6), 411–426. https://doi.org/10.1016/j.appdev.2007.06.010

Morgan, P. L., Farkas, G., Hillemeier, M. M., & Maczuga, S. (2016). Science achievement gaps begin very early, persist, and are largely explained by modifiable factors. *Educational Researcher*, *45*(1), 18–35. https://doi.org/10.3102/0013189X16633182

Muthén, L. K., & Muthen, B. (2017). *Mplus user's guide: Statistical analysis with latent variables, user's guide*.

National Institute of Child Health and Human Development Early Child Care Research Network. (2000). The relation of child care to cognitive and language development. *Child Development*, *71*(4), 960–980. https://doi.org/10.1111/1467-8624.00202

National Institute of Child Health and Human Development Early Child Care Research Network, & Duncan, G. J. (2003). Modeling the impacts of child care quality on children's preschool cognitive development. *Child Development*, *74*(5), 1454–1475. https://doi.org/10.1111/1467-8624.00617

Pantoya, M. L., Aguirre-Munoz, Z., & Hunt, E. M. (2015). Developing an engineering identity in early childhood. *American Journal of Engineering Education*, *6*(2), 61–68. https://doi.org/10.19030/ajee.v6i2.9502

Parker, E., Diffey, L., & Atchinson, B. (2018). *How states fund pre-k: A primer for policymakers*. Education Commission of the States. https://files.eric.ed.gov/fulltext/ED582927.pdf

Perkins, R., Kleiner, B., Roey, S., & Brown, J. (2004). *The high school transcript study: a decade of change in curricula and achievement, 1990–2000* (NCES 2004-455). National Center for Education Statistics.

Pianta, R. C., La Paro, K. M., & Hamre, B. K. (2008). *Classroom assessment scoring system™: Manual K-3*. Paul H Brookes Publishing.

Schaefer, E., & Egarton, M. (1985). Parental and child correlates of parental modernity. In I. E. Sigel (Ed.), *Parental belief systems: The psychological consequences for children* (pp. 287–318). Lawrence Erlbaum.

Schweinhart, L. J., Montie, J., Xiang, Z., Barnett, W. S., Belfield, C. R., & Nores, M. (2005). Lifetime effects: The high/scope Perry preschool study through age 40. *Monographs of the High/Scope Educational Research Foundation*, *14*(3/4), 194–215. https://doi.org/10.1080/09500790008666969

Tout, K., Starr, R., Soli, M., Moodie, S., Kirby, G., & Boller, K. (2010). *Compendium of quality rating systems and evaluations* (No. e3e1472c256f4bd49f20ac5b3c962ad7). Mathematica Policy Research.

Valantine, H. A., & Collins, F. S. (2015). National Institutes of Health addresses the science of diversity. *Proceedings of the National Academy of Sciences*, *112*(40), 12240–12242. https://doi.org/10.1073/pnas.1515612112

Vandell, D. L., Belsky, J., Burchinal, M., Steinberg, L., Vandergrift, N., & the NICHD Early Child Care Research Network. (2010). Do effects of early child care extend to age 15 years? Results from the NICHD study of early child care and youth development. *Child Development*, *81*(3), 737–756. https://doi.org/10.1111/j.1467-8624.2010.01431.x

Vandell, D. L., Burchinal, M., & Pierce, K. M. (2016). Early child care and adolescent functioning at the end of high school: Results from the NICHD study of early child care and youth development. *Developmental Psychology*, *52*(10), 1634–1645. https://doi.org/10.1037/dev0000169

Vandell, D. L., Lee, K. T., Whitaker, A. A., & Pierce, K. M. (2020). Cumulative and differential effects of early child care and middle childhood out-of-school time on adolescent functioning. *Child Development*, *91*(1), 129–144. https://doi.org/10.1111/cdev.13136

Weiland, C., & Yoshikawa, H. (2013). Impacts of a prekindergarten program on children's mathematics, language, literacy, executive function, and emotional skills. *Child Development*, *84*(6), 2112–2130. https://doi.org/10.1111/cdev.12099

Xu, Y. J. (2013). Career outcomes of STEM and non-STEM college graduates: Persistence in major-field and influential factors in career choices. *Research in Higher Education*, *54*(3), 349–382. https://doi.org/10.1007/s11162-012-9275-2

Received February 11, 2022
Revision received February 19, 2023
Accepted February 22, 2023 ■