2017-07-01

Family Environments and Children's Cognitive Skills: Accounting for Heritable Influences Through Comparing Adopted and Biological Children

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A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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ABSTRACT

Family Environments and Children's Cognitive Skills: Accounting for Heritable Influences Through Comparing Adopted and Biological Children

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Utilizing ECLS-K:2011 data, this study compares adopted and biological children to account for the role of heritable characteristics in explaining the relationship between family environments and children's cognitive skills. I find that cognitive skills do not differ across adopted and biological children after adjusting for the systematic differences between them. I also find that the relationship between family environment and children's cognitive skills does not differ across adopted and biological children. Taken together, these results suggest that the relationship between family environment and children's cognitive skills is not spurious.

Keywords: children's cognitive skills, cognitive skill development, family environment, heritable characteristics, social policy

ACKNOWLEDGEMENTS

I thank Brigham Young University for the opportunity to pursue a master's degree in Sociology. This work would not have been possible without the support of numerous administration and staff employed throughout the university or the generous financial support of Graduate Studies and the Department of Sociology.

I am grateful for all of those at Brigham Young University whom I have had the pleasure to work during this and other related projects, including Dr. John Patrick Hoffmann, Dr. Jonathan A. Jarvis, and Margaret McCabe. I am especially indebted to Dr. Kristie J. Rowley, Chair of my thesis committee, and Dr. Mikaela J. Dufur, Graduate Coordinator of the Department of Sociology and member of my thesis committee, who have been supportive of my career goals and who worked actively to provide me with quality academic training to pursue those goals. As my advisors, mentors, and friends, they have both provided me extensive professional and personal guidance and taught me by example a great deal about scientific research and life in general. Thank you, Kristie, for always believing in me when I didn't believe in myself and for advising me to apply to Vanderbilt University. Thank you, Mikaela, for advising me as an undergraduate student to live my life "outside the box" of typical expectations.

I am also grateful for the unending love and support of my family. I would like to thank my parents, Kent and Dusty Jorgensen, for the countless ways in which they have enabled me to complete this work. They have assisted me more than I could ever give them credit for. Most importantly, I wish to thank my husband, Chris McNeill, who supports me in all my adventures through life.

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Research has consistently found large differences in cognitive skills between groups of children (Duncan and Magnuson 2011; Entwisle et al. 1998; Farkas and Beron 2004; Hart and Risley 1999; Lee and Burkham 2002; Phillips et al. 1998). These differences appear prior to enrollment in formal schooling (Farkas and Beron 2004; Hart and Risley 1999) and perpetuate into achievement gaps at school entry (Duncan and Magnuson 2011; Farkas and Beron 2004; Phillips et al. 1998; Lee and Burkam 2002). In turn, these gaps in cognitive skill development have been found to continue and even increase as children move through school (Entwisle et al. 1998; Phillips et al. 1998) and contribute to unequal educational, economic, and social outcomes across the life course (Heckman 2006).

For understanding the mechanisms associated with children’s cognitive skill development, the standard family environment model (Amato and Cheadle 2008) has been the perspective used most by social scientists. The model specifically assumes that the quality of the environments that parents foster or create for their family directly influences children’s outcomes. Social science studies have typically found support for the standard family environment model through demonstrating that specific aspects of children’s family environments (i.e. socioeconomic status, learning tools, etc.) influence their cognitive skill development (Crosnoe and Cooper 2010; Galindo and Sonnenschein 2015). Based on these findings, policy efforts have often focused on mitigating differences in children’s family environments in attempts to reduce cognitive skill gaps.

In recent years, a new perspective, referred to as the passive genetic model (Amato and Cheadle 2008), has improved upon the standard environment model. Based on behavioral genetic research which has found that genetic traits passed on from parents to their biological children (i.e. heritable characteristics) directly influence children's outcomes (Joseph 2014; Plomin et al. 1997), the passive genetic model examines whether the association between family environments and children's outcomes is spurious through accounting for the role of heritable characteristics in explaining the relationship between family environments and children's outcomes. To empirically test the passive genetic model, researchers typically compare outcomes across biological children (who share both family environment and heritable characteristics with their parents) and adopted children (who share only family environments with their parents) (Brodzinsky, Hitt, and Smith 1993; O'Conner et al. 2000). However, social research has not empirically tested the passive genetic model in relation to children's cognitive skill development. As a result, it is unclear whether family environments directly influence children's cognitive skill development and thus whether policy efforts should focus on such environments in order to reduce cognitive skill gaps.

In order to better understand the mechanisms associated with children's cognitive skill development, this study offers a test of the passive genetic model. Utilizing data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011), I specifically compare adopted and biological children to account for the role of heritable characteristics in explaining the relationship between family environments and children's cognitive skills.

REVIEW OF STANDARD FAMILY ENVIRONMENT & PASSIVE GENETIC MODELS

The Standard Family Environment Model

The standard model that is most commonly used by social scientists when studying children's outcomes broadly posits that the quality of the environments that parents foster or create for their families directly influences children's outcomes. This perspective, referred to as the standard family environment model (Amato and Cheadle 2008), specifically assumes that some parents foster “less than optimal settings for children’s socialization and development” (p. 1140). In turn, exposure to these environments directly increases the risk of less than optimal outcomes for children. To empirically test the standard family environment model, social science researchers examine whether various aspects of family environments have a direct influence on children’s outcomes. To facilitate this research, researchers typically utilize large-scale datasets that contain hundreds of measures of family characteristics, as well as advanced statistical software that can accurately analyze relationships between multiple variables.

In regards to cognitive skill development, social science research has generally found support for the standard environment model through demonstrating that various aspects of family environments directly influence children’s cognitive skills. For example, many studies have found that family socioeconomic status (SES) directly influences children’s cognitive skill development (Duncan and Magnuson 2011; Lee and Burkham 2002; Phillips et al. 1998). Children from low-SES families have been found to score more than a standard deviation below children from high-SES families on standardized tests of math and reading when they enter kindergarten and these differences appear to expand as children progress through school (Duncan and Magnuson 2011). In addition, more micro-level aspects of family environments, such as the learning environments that parents foster for their children or parents’ expectations for their children’s present and future development, have also been shown to directly influence cognitive skill development (Crosnoe and Cooper 2010; Fan and Chen 2001; Galindo and Sonnenschein 2015). Growing up in a cognitively stimulating learning environment, which has typically been defined as including a broad array of activities and interactions with others (Caldwell and Bradley 1984) predicts children’s immediate- and long-term cognitive skill development (Crosnoe and Cooper 2010; Galindo and Sonnenschein 2015). Parents’ expectations for their children's future educational attainment has also been found to account for more of the variance in children's cognitive skills than other measures of parental involvement (Fan and Chen 2001).

Utilizing the above findings regarding cognitive skill development, policy efforts have often focused on improving children's family environments in order to reduce differences in children's cognitive skills. Examples of such policy efforts include supplementing the incomes of lower-income families, increasing access to learning tools in children's homes, and offering classes that increase parents' knowledge of how to actively stimulate their child's cognitive skill development (Haskin and Rouse 2005; Kagan and Rigby 2003; Kober 2001). While in general the effectiveness of reducing differences in children's cognitive skills through such policy efforts has been mixed (Chubb and Loveless 2004), the success of some policy efforts has lead to the conclusion that gaps in cognitive skills can be reduced, though not entirely eliminated, through mitigating differences in children's family environments.

The Passive Genetic Model

As stated above, the standard family environment model examines the direct relationship between family environment and children's cognitive skills. While this model is still overwhelming used in social science research for understanding the mechanisms associated with children's outcomes, more recent work has improved upon the standard environment model by identifying the possibility of heritable influences explaining the relationship between family environments and children's cognitive skills. Specifically, behavioral genetic research has found that parents' genetic traits influence various aspects of the family environments that they create, including parenting practices, parental educational level, income, and social support (Kendler and Baker 2007). In addition, behavioral genetic research has also demonstrated that genetic traits passed on from biological parents to their biological children (i.e. heritable characteristics) are associated with children’s outcomes, including personality traits, social behaviors, and cognitive skill development (Joseph 2014; Plomin et al. 1997). These findings imply that heritable characteristics directly influence children’s outcomes, whereas family environments are merely associated with children’s outcomes through heritable characteristics. In other words, the relationship between family environment and children's outcomes could be either partially or completely spurious if heritable characteristics are the direct mechanism connecting family environments and children’s outcomes. Therefore, a new perspective, referred to as the passive genetic model (Amato and Cheadle 2008), examines whether the association between family environment and children’s outcomes is spurious through accounting for the role of heritable characteristics in explaining the relationship between family environments and children’s outcomes. As a result, the passive genetic model improves upon the standard environment model by not only accounting for the direct association between family environment and children’s outcomes, but also for the influence of heritable characteristics in explaining this association.

Due to the difficulties associated with identifying and linking specific heritable traits with children’s outcomes, researchers typically compare outcomes across adopted and biological children to empirically test the passive genetic model. The rationale for this design is that in biological families, parents and children share both heritable and family environments, whereas in adoptive families, parents and children share only family environments. As such, the association between family environment and an outcome for adoptive children represents entirely environmental influences, uncontaminated by heritable influences (Joseph 2014; Plomin et al. 1997). Because adopted and biological children are often raised in systematically different family environments (i.e. adopted children are more likely to be racial minorities and raised in economically and socially advantaged families) (Vandivere, Malm, and Radel 2009), researchers often first account for these systematic differences using regression, matching, or weighting techniques (Imbens 2004). If adopted and biological children have differing outcomes after statistically controlling for systematic differences between them, then shared heritable influences are implicated. This conclusion is warranted because the key remaining difference between adopted and biological children is that biological children share heritable characteristics with their families. Therefore, the relationship between family environment and children's cognitive skills is either completely or partially spurious. However, if both adopted and biological children demonstrate similar outcomes after adjusting for the systematic differences between them, then shared heritable influences are not implicated. Thus, the relationship between family environment and children's outcomes is not spurious.

While a few studies have tested the passive genetic model in relation to children's behavioral problems (Amato and Cheadle 2008; Brodzinsky, Hitt, and Smith 1993; O'Conner et al. 2000), social science research has not empirically tested the passive genetic model when examining children's cognitive skill development. As a result, it is unclear whether family environments are directly influencing children's cognitive skill development or whether this relationship is spurious. This lack of examination of the passive genetic model in relation to children's cognitive skills has large repercussions when one considers the policy implications of the model. If the relationship between family environment and children's cognitive skills is either partially or completely spurious, then current efforts to reduce cognitive skill gaps through mitigating differences in children's family environments are likely also partially or completely ineffective. Thus, determining whether the relationship between family environment and children's cognitive is spurious is crucial to understanding what mechanisms should be the focus of future policy efforts in order to facilitate the largest reductions in children's cognitive skill gaps. Therefore, to provide a test of the passive genetic model in relation to children's cognitive skills, I ask the following research question:

> Q1: After adjusting for the systematic differences between adopted and biological children, do their cognitive skills differ?

An additional test of the passive genetic model can be conducted through examining whether the association between family environment and children's cognitive skills differs across adopted and biological children. If the association between family environment and a child outcome is similar for adopted and biological children, then the relationship between family environment and children's outcomes is not spurious. This conclusion is warranted because adopted children and their adoptive parents do not share heritable characteristics. Therefore, in order for there to be an association between family environment and children's cognitive skills for adopted children, family environment is likely directly influencing children's outcomes. However, by the same logic, if an association between family environment and a child outcome appears among biological children but not among adopted children, then the relationship between family environment and children's cognitive skills is completely spurious. Finally, if an association appears among both groups of children, but the association is stronger for biological than for adopted children, then the relationship between family environment and children's cognitive skills is partially spurious. Therefore, I examine the following research question as a further check of the passive genetic model:

> Q2: Does the relationship between family environment and children's cognitive skills differ across adopted and biological children?

Significance of Study

The present study makes four contributions to the research literature on children's cognitive skill development. First, the current study tests the passive genetic model in relation to children's cognitive skills. Given that few studies have applied this model to the study of cognitive skill development, additional studies that compare adopted and biological children are necessary to draw firmer conclusions regarding whether the relationship between family environment and children's cognitive skills is spurious. The present study contributes to this goal by estimating the influence of family environment on cognitive skills among adopted and biological children sampled from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011). Second, the current study focuses on two measures of children's cognitive skills, mathematics and reading, in order to better assess whether heritable and/or family environment characteristics differentially influence various types of cognitive skills. Third, I use multiple measures of family environment in order to better assess the degree to which heritable characteristics influence specific relationships between family environment and children's cognitive skill development. Lastly, based on my findings regarding the spuriousness of the relationship between family environment and children's cognitive skills, I will be better able to determine what mechanisms should be the focus of future policy efforts in order to facilitate the largest reductions in children's cognitive skill gaps.

METHOD

My study utilizes data from the Early Childhood Longitudinal Study, Kindergarten Class of 2010-2011 (ECLS-K:2011). The ECLS-K:2011 follows a nationally representative sample of over 18,000 children from the fall of kindergarten through the spring of 5th grade. I specifically use the ECLS-K:2011 dataset over other longitudinal studies focused on early childhood due to the significant and representative number of adopted children that were sampled. The study uses direct child assessments to measure children's cognitive skills, as well as parent interviews to learn about children's family environments. My study primarily uses the Fall 2010 kindergarten wave to provide information about children's cognitive skills and their family environmental settings due to younger children having less exposure to other social settings outside of the home, most notably schooling environments, that could influence cognitive skill development.

Analytic Sample

As explained in the literature review, this study compares adopted and biological children to account for the role of heritable characteristics in explaining the relationship between family environment and children's cognitive skills. I therefore limit my analyses to children who were either living with two adoptive parents or two biological parents during the Fall 2010 kindergarten wave. The ECLS-K:2011 defined adoptive parents as parents who have taken a non-biological child into their family by legal process to raise as their own child (U.S. Department of Education 2012). Because of the necessity of adopted children having no genetic relationships with their adoptive parents in my study, children who were adopted by a genetically-related family member (grandparent, aunt/uncle, etc.) were omitted. To create more comparable samples of adopted and biological children, children who did not reside in a two-parent, married, English-speaking household were also omitted from analyses. Lastly, due to this study's focus on children's cognitive skill development, children who did not enroll in school or did not take the standard cognitive skills assessments at the beginning of kindergarten were also dropped from all analyses. This leaves an analytic sample of 7,034 children, of which 183 are adopted children and 6,851 are biological children.

Measures

To address my research questions regarding the role of heritable characteristics in explaining the relationship between family environment and children's cognitive skills, I first created my outcome measures, indicating children's cognitive skills at the beginning of kindergarten. I also created and used control measures, measures of children's characteristics, and measures of children's family environments. Missing data was imputed using similar variables from subsequent waves of the ECLS-K:2011. If data in subsequent waves was also missing, regression imputation was implemented.

Dependent variables

From the ECLS-K:2011 data set, I created measures of children's cognitive skills at the beginning of kindergarten using children's scores on the Fall 2010 kindergarten reading and mathematics assessments. Because children's home environments have been found to differentially influence development of math and reading cognitive skills (Cheadle 2008), I examine the relationship between home environment and both types of skills in my analyses. Both the reading and math assessments were two-stage adaptive tests, with content areas and domains based on the National Assessment for Educational Progress (NAEP) framework (Tourangeau et al. 2015). The reading assessment specifically measures initial understanding, developing interpretation, personal reflection and response, and demonstrating a critical stance. The math assessment measures number sense, properties, and operations; measurement; geometry and spatial sense; data analysis; statistics; and probability, patterns, algebra, and functions. I specifically used the item response theory (IRT) reading and math scale scores, which are criterion-referenced measures of cognitive skills that place children's performance within a common and continuous 64-point scale (Tourangeau et al. 2015). ECLS IRT scale scores have frequently been used as measures of children's cognitive skills in other child development studies (Cheadle 2008; Crosnoe & Cooper 2010; Galindo & Sonnenschein 2015).

Control measures

Because older children and children who take the cognitive skill assessments at later time points in kindergarten have had more time to learn and mature (Burkam et al. 2004; Downey et al. 2004), my control measures include child age and child exposure to kindergarten. Child age was measured as the age (in months) of children when they took the Fall 2010 cognitive skills assessments. Child exposure to kindergarten was measured as the number of months (0 = less than one month to 4 = four months) children had been enrolled in kindergarten when they took the Fall 2010 cognitive skills assessments.

Child characteristics

My measures of child background characteristics include child adoption status, gender, race/ethnicity, stability, and disability. Child adoption status was coded 1 for children who lived with their adoptive parents and 0 for children who lived with their biological parents. Child gender was coded 1 for female and 0 for male. Child race/ethnicity was coded as a series of dummy variables, including white (reference group), black, Hispanic, Asian, and other (which includes Native Hawaiian/Pacific Islander, American Indian/Alaska Native, and multiracial). Child stability was measured as the number of months that a child has lived with their parents. Child disability was coded 1 for children who have been diagnosed with a disability by a professional and/or received therapy services and 0 for children who have not.

Family environment characteristics

Lastly, based on the various ways in which family settings have been shown to influence the cognitive skill development of children (Caldwell & Bradley 1984; Crosnoe and Cooper 2010; Duncan and Magnuson 2011; Fan and Chen 2001; Lee and Burkham 2002; Phillips et al. 1998; Galindo & Sonnenschein 2015), I categorized measures of family environments into three subgroupings: socioeconomic environment, learning environment, and expectational environment. My socioeconomic environment measures include parental level of education, employment status, and income. Parental level of education was measured as the highest level of education (1 = high school degree or less to 4 = post-graduate degree) obtained by either parent. Parental employment status was coded as a series of dummy variables, including neither parent employed, one parent employed, and both parents employed (reference group). Income was measured as the total household income (1 = $25,000 or less to 6 = $200,001 or more).

My measures of learning environments include learning tools, general learning activities, reading learning activities, and parental involvement in school. These variables were created utilizing items from the ECLS-K Fall 2010 and Spring 2011 kindergarten waves and were adapted from the commonly used HOME Inventory (Caldwell and Bradley 1984). Similar scales from the ECLS-K have been used in many published articles (Cheadle 2008; Crosnoe & Cooper 2010; Galindo & Sonnenschein 2015). Learning tools consisted of number of books and CDs in a child's home and whether the child had a computer. The first question was open-ended, and the second question was dichotomous (0 = no, 1 = yes). Therefore, parents' responses to the questions were standardized and then averaged to create a composite scale. General learning activities was created by averaging parents' responses to two questions. Parents reported how often (1 = never to 4 = everyday) they or other family members participated in the following activities with their child: tell stories, sing songs, do art, do chores, play games or do puzzles, talk about nature or do science projects, play sports and build things together or play with construction toys. Parents also reported whether (0 = no, 1 = yes) the child participated in dance lessons, athletic events, organized clubs, music lessons, drama classes, art lessons, organized performing, craft classes, and non-English language instruction outside of school hours. Responses to items within each question were standardized and then averaged.

Reading learning activities was created by averaging parent responses to three questions. Parents reported the frequency (1 =never to 4 = everyday) with which their child looked at picture books, read books by themselves, and read books with others. Parental involvement in school was created by averaging parent responses regarding whether they attended or participated (0 = no, 1 = yes) in various school-related events: open house or back-to-school nights; meetings of PTA, PTO, or parent–teacher–student organization; meetings of the parent advisory group or policy council; regularly-scheduled parent–teacher conferences or meeting with teachers; school or class events; volunteering at the school or serving on a committee; and fundraising for the school.

Lastly, my measures of expectational environments include current educational expectations and future educational expectations. Both of these variables were also created based upon the HOME Inventory scales (Caldwell and Bradley 1984) and are considered to be proxies for parents' academic orientations (Cheadle 2008). To create my measure of current educational expectations, I averaged parent responses to how important (1 = not important to 5 = essential) it was for their child to have the following competencies to be ready for kindergarten: knowing how to count to 20 or more, sharing and taking turns, using pencils and paint brushes, knowing alphabet letters, communicating well, and sitting still and paying attention. Future educational expectations was measured as parent expectations regarding what level of educational attainment they believe their child will attain (1 = high school degree or less to 4 = post-graduate degree). Detailed descriptions of all variables are displayed in Table 1.

(Table 1 about here)

Analytic Design & Strategies

To examine possible differences in control, child, and family environmental characteristics between adopted and biological children, I ran independent sample t-tests. As shown in Table 1 (see Unweighted Statistics), I found that adopted and biological children differed on many of these characteristics (all differences reported here are statistically significant at at least the $p < .05$ level). Biological children were more likely to be white males with no disability and higher math cognitive skills. However, adopted children were more likely to have highly educated parents with higher incomes who are more involved in their children's schooling. These findings were expected, given that non-white, female children are more likely to be adopted and economically and socially advantaged parents are more likely to adopt (Vandivere, Malm, and Radel 2009). However, these significant differences in characteristics between adopted and biological children could lead to biased regression analyses. Regression modeling was designed to only correct for small imbalances in the distribution of covariates between "exposed" and "non-exposed" groups (Fisher 1935). In this study, however, the distribution of characteristics of adopted children differs significantly from the distribution of characteristics of biological children. As such, it is unclear whether a significance test of the "adoption" coefficient sufficiently accounts for the potentially confounding variables.

In order to address the important imbalances and confounding factors that exist in the current sample between adopted and biological children, I employed propensity score weighting. Propensity score weighting provides a mechanism in which bias can be adjusted for through minimizing differences on all covariates between two groups (Hirano, Imbens, and Ridder 2003; McCaffrey, Ridgeway, and Morral 2004; Rosenbaum 1987; Wooldridge 2002). The propensity score for a child is the probability that a child with their set of characteristics is adopted, $p(\mathbf{x})$

$=P(z = 1|\mathbf{x})$. Propensity score weighting reweights biological children so that the distribution of their characteristics matches the distribution of characteristics of adopted children. Assigning weights of $w_i = p(\mathbf{x}_i)/(1 - p(\mathbf{x}_i))$ to each biological child achieves this balance. For example, for biological children with characteristics that are atypical of adopted children, the propensity score would be near 0 and would produce a weight near 0. On the other hand, biological children with characteristics typical of adopted children would receive larger propensity scores and weights.

Other propensity score methods, such as matching and blocking, have been commonly used to minimize differences in covariates between two groups (Imbens 2004). However, recent research has demonstrated that weighting is more effective at adjusting for confounding factors (Lunceford and Davidian 2004). Using propensity score weighting was also ideal for data such as mine where the group of adopted children is smaller than the group of biological children, and many of the biological children could potentially provide good weights. Utilizing and reweighting all available cases also decreases the possibility of discarding important information, which some researchers suggest is common when using only one-to-one matching schemes (Rosenbaum 1995).

The propensity score weights were estimated using Leuven and Sainesi's (2003) "psmatch2" module for Stata-14 statistical software. The propensity score weighting specification included all child characteristics and family environmental characteristics mentioned above.[1] I specifically used the Epanechnikov kernel matching algorithm to weight

[1] Child stability was not included in the propensity score weighting specification due to its high correlation with child adoption status. Because omitting other variables related to the outcome can increase bias in resulting estimates (Heckman, Ichimura, and Todd 1997), the propensity score specification also included the additional measures of whether or not child was a first time kindergartener, child approaches to learning, child internalizing behaviors, child externalizing behaviors, child body mass index (BMI), number of siblings, child care pre-kindergarten, maternal age, and parental occupational prestige. I also controlled for these variables in my initial analyses; however, they were not important predictors and thus were only included in the propensity score specification.

the contribution of each biological child according to the distance between their propensity score and the propensity score of each adopted child. I also used a common-support condition, which omits adopted children whose propensity scores do not match with the propensity score of a biological child within a specified interval. Seven adopted cases were considered "off support" and were omitted from my analyses. To check the quality of the propensity score weighting, I ran individual sample t-test results comparing adopted and biological children after applying the propensity score weights (see Table 1, Propensity Score Weighted Statistics). Because there were no notable differences in covariates between adopted and biological children after applying the weights, I conclude that the propensity score weighting was successful.

Analyses

With propensity score analyses, the final outcomes analysis is generally straightforward. Once propensity score weights are calculated, they are applied to the models being run. Specific to this study, I seek to examine whether children's math and reading cognitive skills differ across adopted and biological children after statistically adjusting for the systematic differences between them. To accomplish this, I run propensity score weighted multivariate linear regression models that include all control, child, and family environment characteristics mentioned above.[2] Coefficients from these models are interpreted in the same way as coefficients from standard multivariate linear regression models. In addition to the models described above, I also run separate models that test whether the relationship between family environments and children's reading and math cognitive skills differs across adopted and biological children. To accomplish this, I include interactions between child adoption status and family environmental

[2] Children sampled in the ECLS-K:2011 dataset are nested within schools. However, due to the unique sampling strategy of my study, the children included in my analytic sample were no longer nested within schools. As such, I use multivariate regression models, as opposed to hierarchical linear models, in my analyses.

characteristics to the models described above. These interactions were first included in the models one at a time to avoid issues with multicollinearity. Due to the interaction terms and their statistical significance not differing in meaningful ways whether interactions were included one at a time, in groupings, or altogether, I report the full reading and math models that include all interaction terms for parsimony. If interactions between child adoption status and family environmental characteristics are significant, I will conclude that the relationship between family environments and children's cognitive skills does differ across adopted and biological children. However, if interactions between child adoption status and family environmental characteristics are not significant, I will conclude that the relationship between family environments and children's cognitive skills does not differ across adopted and biological children.

A combination of propensity score weighting and regression modeling is appropriate for my analyses for several reasons. First, the relationships between many of the covariates and outcome measures are integral to answering my research questions. Including covariates in the propensity score weighted regression models, not just the propensity score weighting model, can provide coefficients that can estimate the direction and magnitude of these relationships (Ridgeway 2006). Second, the propensity score weights may not have been able to completely balance out all of the covariates. The inclusion of these covariates in the propensity score weighted regression model may correct this if the imbalance is relatively small (Tita and Ridgeway 2007; Ridgeway 2006). Lastly, recent research has shown that the inclusion of covariates can make the treatment effect estimate more robust in the sense that if either the propensity score model is correct or the regression model is correct, then the treatment effect estimator will be unbiased (Bang and Robins 2005). These "doubly robust" estimators protect against model misspecification that can be problematic for both regression modeling and propensity score modeling.

RESULTS

Multivariate Models

To test whether children's cognitive skills differ across adopted and biological children after statistically adjusting for the systematic differences between them, I ran propensity score weighted multivariate linear regression models predicting children's reading and math cognitive skills at the beginning of kindergarten. From these analyses, I was able to identify the role of heritable characteristics in explaining the relationship between family environment and children's cognitive skills.

Reading cognitive skills at the beginning of kindergarten

When predicting the reading cognitive skills of children at the beginning of kindergarten (see Table 2, Model 1), both control measures were statistically significant. Child age at assessment was positively related to reading cognitive skills ($\beta = 0.265$, $p < .001$), as was child exposure to kindergarten ($\beta = 1.502$, $p < .01$). Three child characteristics also yielded significant results. On average, children of other races had higher reading cognitive skills than white children ($\beta = 2.372$, $p < .05$). Children who have a disability had lower reading cognitive skills on average than students without a disability ($\beta = -3.401$, $p < .001$). Child stability was also positively related to reading cognitive skills ($\beta = 0.087$, $p < .01$). Specific to my research question, child adoption status was not significantly related to children's reading cognitive skills. Child gender and differences in reading cognitive skills for black, Hispanic, and Asian children compared to white children also were not statistically significant.

I also found that three characteristics of children's family environments were statistically significant. In regards to socioeconomic environments, parental level of education was significantly related to reading cognitive skills. On average, children whose parents obtained a high school degree or less had lower reading cognitive skills than children whose parents obtained a Bachelor's degree (β = -4.429, $p < .01$). This relationship accounted for 15 percent of a standard deviation in children's reading cognitive skills at the beginning of kindergarten, yielding one of the largest effects in the model.[3] Parental employment status and income did not yield statistically significant results. In regards to learning environments, reading learning activities were also positively related to reading cognitive skills. A one-unit increase in reading learning activities was associated with a 2.759-point increase in children's achievement on the reading cognitive skills assessment at the beginning of kindergarten ($p < .001$). This relationship also accounted for 15 percent of a standard deviation in children's reading cognitive skills at the beginning of kindergarten. Learning tools, general learning activities, and parental involvement in school did not yield statistically significant results.

In addition, both measures of expectational environments were significantly associated with higher reading cognitive skills. Every one-unit increase in current educational expectations was associated with a 1.978-point increase in children's achievement on the reading cognitive skills assessment at the beginning of kindergarten ($p < .01$). Similarly, every one-unit increase in future educational expectations was associated with a 1.229-point increase in achievement on the reading cognitive skills assessment ($p < .05$). Both current educational expectations and future educational expectations accounted for 11 percent of a standard deviation in children's reading cognitive skills at the beginning of kindergarten.

[3] Effect sizes were determined by multiplying the coefficient by its standard deviation and then dividing the product by the standard deviation of the dependent variable.

(Table 2 about here)

Math cognitive skills at the beginning of kindergarten

I obtained similar results from the control and child characteristics portions of my full model predicting children's math cognitive skills at the beginning of kindergarten (see Table 2, Model 3). All control and child characteristic measures that yielded statistically significant results when predicting children's reading cognitive skills were also significant when predicting children's math cognitive skills. In addition, two measures of child race/ethnicity were statistically significant in the math model. On average, Hispanic children had lower math cognitive skills than white children (β = -2.232, $p < .05$). In contrast, Asian children had higher math cognitive skills than white children (β = 2.401, $p < .05$). Related to my research question, child adoption status was not significantly related to children's math cognitive skills.

Similar to the findings of my reading cognitive skills model, I found that parental level of education, reading learning activities, and future educational expectations were significant predictors of children's math cognitive skills at the beginning of kindergarten. Children whose parents obtained a high school degree or less again yielded the largest effect in the model, accounting for 17 percent of a standard deviation in children's math cognitive skills at the beginning of kindergarten. Future educational expectations also accounted for 10 percent of a standard deviation in children's math cognitive skills. In contrast to my reading cognitive skills model, children whose parents obtained some college or a technological degree had significantly lower math cognitive skills than children whose parents obtained a Bachelor's degree (β = -2.645, $p < .05$). Also in contrast to my reading cognitive skills model, current educational expectations was not a significant predictor of children's math cognitive skills at the beginning of kindergarten. Parent employment status, income, learning tools, general learning activities, and parental involvement in school again did not yield statistically significant results.

Differences in relationships by adoption status

To test whether the relationship between family environment and children's cognitive skills differs across adopted and biological children, I ran two additional models that include all interactions between child adoption status and family environment (see Table 2, Models 2 and 4). None of the interaction terms in either model were significant predictors of children's reading or math cognitive skills. Based on the above findings, I conclude that the relationship between family environment and children's cognitive skills does not differ across adopted and biological children.

Cumulative Effect of Children's Family Environments

To further demonstrate the degree to which family environments contributed to differences in children's reading and math cognitive skills, I used the results of my multivariate models (Models 1 and 3) to calculate outcomes based on varying levels of parents' level of education and future educational expectations. These two family environment characteristics yielded the largest effects in both my reading and math cognitive skill models. Figure 1 highlights these results. Children whose parents have a high school degree or less and future expectations of a high school degree or less for their child had below average cognitive skill scores in both reading and math. In contrast, children whose parents have a Bachelor's degree and future expectations of a Bachelor's degree for their child had above average reading and math cognitive skill scores. The difference in cognitive skill scores between these two groups of children was roughly seven to eight points for both reading and math. This difference approximately equates to 70 percent of a standard deviation in both reading and math cognitive skill scores. Furthermore, for an average child taking the ECLS-K reading and math cognitive skill tests, one-point roughly equates to the amount a child learned in 2 weeks of school (Rock and Pollack 2002). Thus, the difference in reading and math cognitive skill scores between these two groups of children can also be interpreted as being roughly equal to the amount learned in 14 to 16 weeks, or half a year, of school.

(Figure 1 about here)

DISCUSSION

Support for Family Environmental Influences

This study contributes to the social science literature by testing the passive genetic model in relation to children's cognitive skill development. Utilizing ECLS-K:2011 data, I specifically compared adopted and biological children to account for the role of heritable characteristics in explaining the relationship between family environment and children's cognitive skills. I found that reading and math cognitive skills did not differ across adopted and biological children after statistically adjusting for the systematic differences in family environment between them. Because adopted and biological children demonstrated similar levels of cognitive skill development, heritable influences were not implicated. Therefore, this finding implies that the relationship between family environment and children's cognitive skills is not spurious.

Through analyzing interactions between child adoption status and family environments, I also found that relationships between family environmental characteristics and children's reading and math cognitive skills did not differ across adopted or biological children. This finding further suggests that the relationship between family environment and children's cognitive skills is not spurious. This conclusion is warranted because adopted children and their adoptive parents do not share heritable characteristics. Therefore, in order for there to be an association between family environment and children's cognitive skills for adopted children, family environment is likely directly influencing children's cognitive skills. As such, I more definitively conclude that family environment is directly influencing children's cognitive skill development.

Lastly, this study examined which family environment characteristics were significantly associated with children's cognitive skills. I specifically found that obtaining a high school degree or less, reading learning activities, and future educational expectations were significantly associated with both children's reading and math cognitive skills, with the initial characteristic yielding the largest effect on both skills. Current educational expectations was only significantly related to children's reading cognitive skills, and obtaining some college or a technological degree was only significantly related to children's math cognitive skills. These findings are consistent with many social science studies that have demonstrated the direct influence of these characteristics on children's cognitive skill development (Crosnoe and Cooper 2010; Duncan and Magnuson 2011; Fan and Chen 2001; Galindo and Sonnenschein 2015; Lee and Burkham 2002; Phillips et al. 1998). However, I also found that parental employment status, income, learning tools, general learning activities, and parental involvement in school were not significantly associated with children's cognitive skills. While the relatively high level of family income and parental involvement in school of our sample may have contributed to these specific factors not being statistically significant, these findings suggest that not all aspects of family socioeconomic and learning environments are meaningfully related to children's cognitive skill development.

Policy Implications

My results have important implications for future social and educational policy, especially in relation to reducing differences in children's cognitive skills. Most notably, prior to this study, it was unclear whether family environments were directly influencing children's cognitive skill development and thus whether policy efforts should focus on such environments in order to reduce cognitive skill gaps. Through finding that heritable characteristics do not explain the relationship between family environment and children's cognitive skills, I demonstrate that the relationship between family environment and children's cognitive skills is not spurious. Thus, it can reasonably be assumed that policy efforts focused on improving children's family environments will likely mitigate differences in children's cognitive skills. Further, because family environments influence children's cognitive skills regardless of whether children share heritable characteristics with their parents, policy efforts to improve family environments are likely to be influential across all types of family structures (i.e. biological, step-parent, foster, etc.). Therefore, improving family environments can be expected to influence most children's development of cognitive skills.

My findings regarding which family environment characteristics are associated with children's cognitive skills should also be taken into consideration when making policy decisions. Specifically, although social policy efforts have often focused on decreasing differences in children's cognitive skills through increasing access to learning tools in children's homes or supplementing the incomes of lower-income families (Haskin and Rouse 2005; Kagan and Rigby 2003; Kober 2001), neither of these family environmental characteristics were significant predictors of children's cognitive skills in this study. Rather, parental level of education (specifically obtaining a high school degree or less) was the strongest predictor of both children's reading and math cognitive skills. These findings suggest that short-term policy efforts aimed at increasing the resources in children's family environments are unlikely to significantly improve children's cognitive skills. Instead, more long-term, intergenerational policy efforts that can facilitate more students graduating from high school and obtaining higher education are most likely to lead to the largest reductions in children's cognitive skill gaps. Due to the strong relationship between parents' education and the quality of learning and expectational environments they create for their children (Magnuson et al. 2009), policy efforts to increase educational attainment would also likely improve the quality of other aspects of children's family environments as well. Thus, based on the findings of this study, implementing long-term policy efforts that increase parental levels of education should be one of the primary focuses of social and educational policy in order to most effectively reduce differences in children's cognitive skills.

Limitations

While this study draws important conclusions about the role of heritable characteristics in explaining the relationship between family environment and children's cognitive skills, it is not without limitations. Foremost, I acknowledge that the relationships we examine here cannot be fully understood from any single study. I also recognize that neither the ECLS-K:2011 data nor this study can fully account for all the possible mechanisms that could be influencing children's math and reading cognitive skills at the beginning of kindergarten. In addition, I also acknowledge that the associations identified in this study cannot definitively prove causal explanations regarding children's cognitive skill development. Finally, I recognize that although this study found that the relationship between family environment and children's cognitive skills is not spurious, the passive genetic model should not be disregarded. Due to the limited number of social science studies that have accounted for heritable characteristics when studying the association between family environment and children's cognitive skill development, future research should study these relationships further.

CONCLUSION

In conclusion, the present study is one of the first to empirically test the passive genetic model in relation to children's cognitive skill development. The analysis suggests that the influence of family environment on children's cognitive skills does not differ across adopted and biological children. Furthermore, this relationship is similar for adopted and biological children across both reading and math cognitive skills, as well as across multiple measures of family environment. Based on these findings, I conclude that the relationship between family environment and children's cognitive skills is not spurious. Importantly, this study also found that multiple aspects of family environments are associated with children's cognitive skill development, including parental level of education, reading learning activities, and future educational expectations. Because parental level of education yielded the largest effect on both children's math and reading cognitive skills, long-term, intergenerational policy efforts that can facilitate more students obtaining higher education are needed to foster the largest reductions in children's cognitive skill gaps in the future.

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TABLES

Table 1. Description of Variables[a]

Variables	Unweighted Statistics: BIOLOGICAL CHILDREN Mean	Unweighted Statistics: ADOPTED CHILDREN Mean	Sig.	Propensity Score Weighted Statistics: FULL SAMPLE Mean	FULL SAMPLE SD	BIOLOGICAL CHILDREN Mean	BIOLOGICAL CHILDREN SD	ADOPTED CHILDREN Mean	ADOPTED CHILDREN SD
Dependent Variables: Reading and Mathematics Cognitive Skills									
Reading Cognitive Skills	40.10	38.69		39.52	10.01	40.21	11.39	38.83	8.37
Item response theory (IRT) reading scale scores from the fall of kindergarten									
Mathematics Cognitive Skills	34.03	32.37	*	33.11	10.83	33.65	11.39	32.58	10.24
Item response theory (IRT) math scale scores from the fall of kindergarten									
Controls									
Child Age at Assessment	67.56	68.30	*	67.85	4.61	67.48	4.38	68.23	4.80
Age (in months) of child when they took the math and reading assessments									
Child Exposure to Kindergarten at Assessment	2.17	2.08		2.14	0.96	2.20	0.99	2.09	0.93
Number of months in kindergarten when child took the math and reading assessments									
Child Characteristics									
Child Adoption Status									
Coded as: Child Lives with Biological Parents = 0	1.00	0		0.97	—	1.00	—	0.00	—
Child Lives with Adoptive Parents = 1	0.00	1.00		0.03	—	0.00	—	1.00	—
Child Gender									
Coded as: Male = 0	0.51	0.43	*	0.45	—	0.46	—	0.43	—
Female = 1	0.49	0.57	*	0.55	—	0.54	—	0.57	—
Child Race/Ethnicity									
Coded as: White	0.68	0.35	***	0.37	—	0.38	—	0.36	—
Black	0.06	0.08		0.07	—	0.07	—	0.07	—
Hispanic	0.06	0.20	***	0.20	—	0.20	—	0.20	—
Asian	0.05	0.28	***	0.26	—	0.25	—	0.28	—
Other	0.15	0.09	*	0.10	—	0.10	—	0.09	—
Child Stability									
Number of months child has lived with parents	67.57	53.90	***	60.76	14.11	67.47	4.42	54.06	17.04
Child Disability									
Coded as: No Disability Diagnosis/Therapy = 0	0.81	0.67	***	0.70	—	0.72	—	0.68	—
Has Disability Diagnosis/Received Therapy = 1	0.19	0.33	***	0.30	—	0.28	—	0.32	—

Table 1 (cont.). Description of Variables[a]

	Unweighted Statistics			Propensity Score Weighted Statistics					
	BIOLOGICAL CHILDREN	ADOPTED CHILDREN		FULL SAMPLE		BIOLOGICAL CHILDREN		ADOPTED CHILDREN	
Variables	**Mean**	**Mean**	**Sig.**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Family Environment Characteristics									
Socioeconomic Environment									
Parental Level of Education									
Coded as: High school Degree or Less	0.12	0.12		0.14	—	0.17	—	0.11	—
Some College or Technical Degree	0.29	0.13	***	0.15	—	0.16	—	0.14	—
Bachelor's Degree	0.33	0.36		0.34	—	0.32	—	0.35	—
Post-Graduate Degree	0.26	0.39	***	0.37	—	0.35	—	0.40	—
Parental Employment Status									
Coded as: Neither Parent Employed	0.02	0.02		0.01	—	0.01	—	0.01	—
One Parent Employed	0.36	0.40		0.39	—	0.40	—	0.39	—
Both Parents Employed	0.62	0.58		0.60	—	0.59	—	0.60	—
Income	3.55	4.06	***	4.03	1.38	3.98	1.44	4.08	1.31
Coded as: $25,000 or Less = 1									
$25,001 - $50,000 = 2									
$50,001 - $75,000 = 3									
$75,001 - $100,000 = 4									
$100,001 - $200,000 = 5									
$200,001 or More = 6									
Learning Environment									
Learning Tools *(2 item composite standardized mean; α = 0.09)*	-0.01	0.00		0.00	0.67	0.01	0.64	0.02	0.70
Number of books and CDs in child's home									
Coded as: 0 to 200+									
Child has computer in home									
Coded as: No = 0									
Yes = 1									
General Learning Activities *(17 item composite standardized mean; α = 0.63)*	0.01	-0.02		0.00	0.44	-0.02	0.48	0.01	0.40
How often parents or other family members participate in activies (e.g., tell stories, play games or puzzles) with child									
Coded as: Not at All = 1									
Once or Twice a Week = 2									
Three to Six Times a Week = 3									
Everyday = 4									
Child participtes in extracurricular activities (e.g., dance lessons, music lessons, athletic events)									
Coded as: No = 0									
Yes = 1									

Table 1 (cont.). Description of Variables[a]

Variables	Unweighted Statistics: BIOLOGICAL CHILDREN Mean	Unweighted Statistics: ADOPTED CHILDREN Mean	Sig.	Propensity Score Weighted Statistics: FULL SAMPLE Mean	FULL SAMPLE SD	BIOLOGICAL CHILDREN Mean	BIOLOGICAL CHILDREN SD	ADOPTED CHILDREN Mean	ADOPTED CHILDREN SD
<u>Learning Environment (cont.)</u>									
Reading Learning Activities *(3 item composite mean; α = 0.63)*	3.32	3.40		3.36	0.55	3.33	0.58	3.39	0.52
How often child looks at picture books, reads books by themselves, and reads books with others									
Coded as: Not at All = 1									
Once or Twice a Week = 2									
Three to Six Times a Week = 3									
Everyday = 4									
Parental Involvement in School *(7 item composite mean; α = 0.51)*	0.66	0.72	***	0.69	0.17	0.69	0.19	0.70	0.15
Parent participation in various school-related events (e.g., school or class events, parent-teacher conferences)									
Coded as: No = 0									
Yes = 1									
<u>Expectational Environment</u>									
Current Educational Expectations *(6 item composite mean; α = 0.82)*	4.19	4.07	**	4.08	0.53	4.10	0.51	4.06	0.55
Parents' expectations regarding their child having certain competencies to be ready for kindergarten (e.g., knowing alphabet letters, sharing and taking turns)									
Coded as: Not Important = 1									
Not Very Important = 2									
Somewhat Important = 3									
Very Important = 4									
Essential = 5									
Future Educational Expectations	3.13	3.04		3.01	0.87	2.97	0.96	3.04	0.77
Parents' expectations regarding what level of educational attainment they believe their child will attain									
Coded as: High School Degree or Less = 1									
Some College or Technical Degree = 2									
Bachelor's Degree = 3									
Post-Graduate Degree = 4									
N	*6,851*	*183*		*7,027*		*6,851*		*176*	

[a] Propensity score weighted independent sample t-tests comparing biological and adopted children did not yield any notable findings and thus are not reported

Table 2. Propensity Score Weighted Multivariate Linear Regression Models Predicting Children's Reading & Math Cognitive Skills at the Beginning of Kindergarten

	Reading Cognitive Skills						Math Cognitive Skills					
	Model 1			Model 2			Model 3			Model 4		
Variable List	*coef*	*s.e.*	*p*	*coef*	*s.e.*	*p*	*coef*	*s.e.*	*p*	*coef*	*s.e.*	*p*
Intercept	-8.154	*(6.686)*		-12.058	*(6.889)*		-16.119	*(6.779)*		-14.096	*(6.838)*	
Controls												
Child Age at Assessment	0.265	*(0.075)*	***	0.283	*(0.075)*	***	0.368	*(0.080)*	***	0.374	*(0.083)*	***
Child Exposure to Kindergarten at Assessment	1.502	*(0.434)*	**	1.793	*(0.415)*	***	1.611	*(0.418)*	***	1.656	*(0.425)*	***
Child Characteristics												
Child Adoption Status (ref= Biological)												
Adopted	-0.703	*(0.911)*		5.579	*(7.957)*		0.323	*(0.949)*		-6.138	*(9.427)*	
Child Gender (ref= Male)												
Female	0.191	*(0.838)*		0.476	*(0.841)*		-1.520	*(0.823)*		-1.487	*(0.826)*	
Child Race/Ethnicity (ref= White)												
Black	-0.795	*(1.823)*		-0.875	*(1.762)*		-2.631	*(1.994)*		-2.575	*(1.891)*	
Hispanic	-1.093	*(0.864)*		-0.388	*(0.861)*		-2.232	*(0.927)*	*	-1.950	*(0.964)*	*
Asian	1.548	*(1.207)*		2.144	*(1.154)*		2.401	*(1.176)*	*	2.460	*(1.216)*	*
Other	2.372	*(1.069)*	*	2.607	*(1.079)*	**	2.708	*(1.212)*	*	2.551	*(1.222)*	*
Child Disability (ref= No Disability/Therapy)												
Child has Disability Diagnosis/Received Therapy	-3.401	*(0.785)*	***	-3.645	*(0.763)*	***	-4.817	*(0.926)*	***	-4.950	*(0.915)*	***
Child Stability	0.087	*(0.028)*	**	0.095	*(0.031)*	**	0.099	*(0.034)*	**	0.103	*(0.035)*	**
Family Environment Characteristics												
Socioeconomic Environment												
Parental Level of Education (ref=Bachelor's Degree)												
High School Degree or Less	-4.429	*(1.461)*	**	-5.551	*(1.209)*	***	-5.224	*(1.403)*	***	-5.191	*(1.482)*	***
Some College or Tech Degree	-1.949	*(1.018)*		-2.534	*(0.878)*	**	-2.645	*(1.057)*	*	-2.656	*(1.009)*	**
Post-Graduate Degree	0.762	*(1.031)*		0.620	*(1.336)*		0.774	*(1.075)*		0.546	*(1.186)*	
Parental Employment Status (ref=Both Employed)												
Neither Parent Employed	-1.810	*(1.220)*		-0.898	*(1.274)*		-2.654	*(2.086)*		-5.273	*(1.923)*	**
One Parent Employed	-0.868	*(0.834)*		-0.556	*(0.967)*		-1.083	*(0.897)*		-0.578	*(1.018)*	
Income	0.137	*(0.328)*		0.380	*(0.361)*		0.359	*(0.333)*		0.926	*(0.362)*	**
Learning Environment												
Learning Tools	-0.017	*(0.509)*		0.189	*(0.476)*		0.261	*(0.554)*		0.763	*(0.485)*	
General Learning Activities	-0.623	*(1.125)*		0.989	*(1.326)*		0.293	*(1.047)*		1.752	*(1.196)*	
Reading Learning Activities	2.759	*(0.688)*	***	3.243	*(0.737)*	***	1.618	*(0.758)*	*	1.629	*(0.818)*	*
Parental Involvement in School	2.172	*(2.062)*		2.608	*(1.968)*		4.279	*(2.222)*		2.033	*(2.119)*	
Expectational Environment												
Current Educational Expectations	1.978	*(0.698)*	**	1.349	*(0.832)*		1.148	*(0.839)*		0.338	*(1.018)*	
Future Educational Expectations	1.229	*(0.484)*	*	1.580	*(0.529)*	**	1.238	*(0.486)*	*	1.133	*(0.497)*	*
Interactions Terms												
Child is Adopted X High School Degree or Less				4.020	*(2.667)*					0.044	*(2.744)*	
" " X Some College or Tech Degree				1.314	*(2.012)*					0.382	*(2.124)*	
" " X Post-Graduate Degree				0.606	*(1.919)*					0.197	*(2.113)*	
" " X Neither Parent Employed				-1.432	*(2.657)*					3.483	*(3.466)*	
" " X One Parent Employed				-0.105	*(1.605)*					-1.136	*(1.801)*	
" " X Income				-0.380	*(0.667)*					-1.092	*(0.716)*	
" " X Learning Tools				0.221	*(1.026)*					-0.804	*(1.061)*	
" " X General Learning Activities				-3.875	*(2.097)*					-2.888	*(2.192)*	
" " X Reading Learning Activities				-1.082	*(1.378)*					-0.064	*(1.543)*	
" " X Parental Involvement in School				-3.983	*(4.644)*					4.244	*(5.214)*	
" " X Current Educational Expectations				1.115	*(1.311)*					1.694	*(1.664)*	
" " X Future Educational Expectations				-1.222	*(0.967)*					0.298	*(1.060)*	

P-values reported for two-tailed tests; ****p* < .001; ***p* < .01; **p* < .05

N = 7,027 children

FIGURES

Figure 1. Cumulative Effect of Family Environments on Children's Cognitive Skill Scores