Family Income and School Readiness Skills

Samuel Portnow

B.A., New York University, 2009

M.A., University of Virginia

University of Virginia

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Department of Psychology

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Dissertation Committee:

Melvin N. Wilson, Ph.D., (Chair)

Steve Boker, Ph.D.

Jason Downer, Ph.D. (Curry School of Education)

Luke Miller, Ph.D. (Curry School of Education)

Bethany Teachman, Ph.D.

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Abstract

Quasi-experimental research suggests that additional family income leads to increased child achievement in elementary and high school (Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011; Milligan & Stable, 2011). An additional $1,000 in annual family income corresponds to five-seven percent of a standard deviation increase on standardized reading and math skills in elementary and high school (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). There is some suggestive evidence that increases in income may cause increases in school readiness skills prior to formal schooling, but no research has directly examined the effect of family income on school readiness skills (Duncan et al., 2011). This gap in research is unfortunate because school readiness skills serve as the basis for later child achievement.

The first aim of the proposed dissertation is to examine the effect of family income on school readiness skills; across two separate datasets. Using causal inference techniques, the present dissertation examines whether an additional $1,000 in family income corresponds to an increase in school readiness skills. The proposed dissertation hypothesizes that across each dataset, an additional $1,000 in family income corresponds to an increase in school readiness skills.

The second and third aims of the proposed dissertation examine *how* an additional $1,000 in family income increases school readiness skills. For the second aim, again using

causal inference techniques across two datasets, the present dissertation examines whether parental cognitive stimulation mediates the relation between an additional $1,000 in family income and increased school readiness skills. For the third aim, the present dissertation uses causal inference techniques across to examine childcare as a mediator of the relation between an additional $1,000 in family income and increased school readiness skills. Given the relative lack of research that has examined childcare as a mediator between an additional $1,000 in income and increased school readiness skills, the third aim is exploratory, and there are no a priori hypotheses.

Results indicated that income did indeed increase children's school readiness skills. An additional $1,000 in income corresponded to a .05-.07 SD unit increase in math skills, and a to .09 - .13 SD unit increase in reading skills. Results suggested that neither cognitive stimulation nor childcare quality mediated the relation between income and school readiness skills.

Introduction

Compared to their economically advantaged peers, children in poverty perform more poorly on standardized tests, receive worse grades, and are less likely to complete high school and college (Gamoran, 2001; Ladson-Billings, 2006; Reardon, 2011). Disparities between children in poverty and their economically advantaged peers exist throughout schooling. Beginning with school entry and continuing through graduation, children in the bottom quintile of the income distribution are more than a full standard deviation behind children in the top quintile on reading and math achievement tests (Duncan & Magnusson, 2011).

Converging quasi-experimental evidence suggests an additional $1,000 in annual family income increases children's scores on standardized reading and math tests by five – seven percent of a standard deviation in elementary school and high school (Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011; Milligan & Stable, 2011). These results suggest an additional $4,000 – an amount of increased income often observed in the world either through tax credits or wage increases – would go a long way toward reducing the gap between low income children and their more economically advantaged peers.

School Readiness Skills

Recent policy debates have centered on how to provide high-quality childcare to all children. The hope is that such efforts can ensure that a child comes to their first day of formal schooling prepared to learn, and because they do not have to catch up with their peers, can be set upon their best potential academic trajectory. In order to prepare children to learn on their first day of formal schooling, high quality childcare bolsters children's school readiness skills. For the purposes of the present dissertation, school readiness skills are defined as reading and math skills that serve as the foundation for learning in formal schooling, as well

<u>School Readiness Skills</u>
Reading Skills
Math Skills
General Cognitive Development

as more general indicators of children's cognitive development prior to formal schooling (Duncan et al., 2007). The present dissertation proposes another avenue to boost children's school readiness skills: family income. Although quasi-experimental research suggests that an additional $1,000 of income increases child achievement, to my knowledge, no quasi-experimental research has examined if a $1,000 increase in family income would increase children's school readiness skills. The lack of information on the effect of income is unfortunate because school readiness skills serve as the basis from which later child achievement is built (Duncan et al., 2007).

The first aim of this dissertation addresses the lack of research on the relation between income and school readiness skills. The present dissertation investigates whether additional family income corresponds to an increase in school readiness skills. The second and third aims of the proposed dissertation examine parenting and childcare as mediators of the relation between income and school readiness skills. The ultimate goals of the proposed dissertation are to give an estimate of how much of a gain in school readiness skills could be expected from an additional income and to examine how an additional $1,000 in income may relate to gains in school readiness skills. See Figure 1 for the proposed mediation model.

Debate persisted for years on the relation between income and child achievement. Early research suggested that family income was not causally related to child achievement (Mayer, 1997). Decades later, more definitive evidence, that used instrumental variables estimation, as a opposed to longitudinal fixed effects (the technique employed by earlier research) suggested a causal link (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). The debate on the effect of income on child achievement persisted because of omitted variable bias: income is related to child achievement, but income and child achievement are also related to scores of other variables, such as intelligence, motivation, and school and neighborhood quality, to name a few. It is impossible to control for all these variables in one study – there are simply too many. Omitted variable bias is also the reason why the proposed dissertation uses causal inference techniques. If one were to regress income on to school readiness skills, they could not conclude that additional income would increase school readiness skills, and would be unable to deflect criticism that the observed relation can be explained by an omitted variable.

Causal inference techniques are methods of obtaining causal estimates for non-experimental data that are able to approximate the gold standard of random assignment (Gelman & Hill, 2007; Willett & Murnane, 2010). Because family income is not randomly assigned, researchers have had to rely on causal inference techniques to study the relation between income and child achievement (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). These studies serve as the basis for the hypotheses and analyses of the present dissertation.

Causal Inference Indicates Income Causes Increased Child Achievement: Converging Evidence

Research that uses instrumental variable estimation suggests that an additional $1,000 corresponds to five-to-seven percent of a standard deviation increase in standardized reading and math scores in elementary school (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). An instrumental variable strategy exploits variation in an instrument that is ignorably assigned, in that it does not interact with participant characteristics (e.g., policy change, random assignment to a voluntary job training program). The variation in the instrument is then used to isolate the unbiased effect of a treatment that does interact with participant characteristics (e.g., income, attendance at a voluntary job training) (Gelman & Hill, 2007; Gennetian, Magnusson, & Morris, 2008). If the instrument is ignorably assigned, strongly related to the treatment, and only affects the outcome through the treatment, then instrumental variable estimation approximates a randomized experiment (Shadish, Clark, & Steiner, 2008; Gelman & Hill, 2007). Results become biased when the instrument interacts with participant characteristics, is weakly related to the treatment, or affects the outcome through pathways other than the treatment. For a more detailed explanation of instrumental variable estimation, see the Methods section.

Research has used three different instruments to estimate the impact of family income on child achievement: 1) variation in the Earned Income Tax Credit (EITC) in the U.S., 2) variation in benefits in Canada, and 3) variation in assignment to antipoverty programs in the U.S. In the mid-1990's, there was a dramatic increase in EITC, which provides cash assistance to working families. Research that leveraged this variation found that an additional $1,000 in family income (adjusted to year 2000 dollars) raised combined math and reading test scores by six percent of a standard deviation (Dahl & Lochner, 2012). Research that leveraged exogenous variation in government benefits in Canada across province, family size, and time found similar results: an additional $1,000 in benefits raised standardized math scores by seven percent of a standard deviation (Milligan & Stable, 2011). Finally, research that exploited random assignment to antipoverty programs found the same pattern of results: an additional $1,000 in annual income increased young children's achievement by five-to-seven percent of a standard deviation. (Duncan et al., 2012).

Research that used random assignment to antipoverty programs suggests that an additional $1,000 in family income would also boost school readiness skills: the authors found that an additional $1,000 in family income in preschool corresponded to five-six percent of a standard deviation increase in standardized reading and math scores in elementary school (Duncan et al., 2012). It is possible that with an additional $1,000 in family income, these children had more school readiness skills, and were more prepared to learn in elementary school than their peers whose families did not receive an additional $1,000. The first aim of this dissertation explores this possibility: the present dissertation uses causal inference techniques to investigate the relation between an additional $1,000 and increased school readiness skills. The present dissertation hypothesizes that an additional $1,000 in family income will increase school readiness skills.

The second and third aims of this dissertation address another gap in the research: there is limited evidence to suggest *why* an additional $1,000 in family income may increase school readiness skills. The present dissertation uses causal inference techniques to investigate parenting behaviors and childcare as mediators between income and school readiness skills.

Evidence for Cognitive Stimulation as a Mediator

Parenting behaviors are strong predictors of school readiness skills (Brooks-Gunn & Markman, 2005). The present study focuses on a particular set of parenting behaviors as a potential mediator of the link between income and school readiness skills: cognitive stimulation. In line with previous research, cognitive stimulation is defined as the material goods (e.g., books), activities (e.g., trips to the library), and interactions (e.g., teaching new concepts or asking questions that encourage problem-solving or pretend play) that promote cognitive development (Caldwell & Bradley, 1984; Votruba-Drzal, 2003). To detail how cognitive stimulation might mediate the relation between family income and school readiness skills, the present dissertation draws upon the Family Investment Model.

Cognitive Stimulation
Material Goods (e.g., Books)
Activities (e.g., Trips to library)
Interactions (e.g., Teaching New Concepts)

According to the Family Investment Model, parents must sacrifice purchases, activities, and interactions that promote children's cognitive development, in order to attend to more immediate needs, such as food and shelter (Haveman & Wolf, 1984; Conger & Donnellan, 2007). Substantial literature shows that family income shares a direct, positive relation with cognitive stimulation. For example, parents in poverty read less often to their children, have fewer books in their homes, allow their children to watch more television and go to libraries and museums less often than their more economically advantaged peers (Guo & Harris, 2000; Larson & Verma, 1999; Linver, Brooks-Gunn, & Kohen, 2002).

With an additional $1,000 in family income, parents might engage in more cognitive stimulation, and their children may display more school readiness skills as a result. For example, correlational research has found that cognitive stimulation mediates the relation between income and school readiness skills (Linver et al., 2002; Yeung, Linver, & Brooks-Gunn, 2000). Moreover, quasi-experimental evidence suggests that with additional income, families engage in more cognitive stimulation (Votruba-Drzal, 2003), and experimental evidence suggests that boosting cognitive stimulation results in more school readiness skills (Landry, Smith, Swank, & Guttentag, 2008). The present dissertation extends this research and examines the path from increased cognitive stimulation to increased school readiness skills, as well as the path from additional income to increased school readiness skills (↑ income → ↑ cognitive stimulation → ↑ school readiness skills). The present dissertation hypothesizes that that more cognitive stimulation will mediate the relation between an additional $1,000 in family income and increased school readiness skills.

High Quality Childcare Increases School Readiness

An additional $1,000 in family income may also increase school readiness skills through childcare: families with an additional $1,000 in family income may be able to purchase higher quality childcare, which may in turn increase school readiness skills (Howes et al., 2008). In the proposed dissertation, high-quality childcare is childcare from birth to kindergarten that provides supportive interactions between children, caregivers, and teachers, in addition to intentional instruction (Pianta, Barnett, Burchinal, & Thornburg, 2009). Two of the most famous high quality programs are the Perry Preschool and the Carolina Abecedarian Project. The Perry Preschool provided one-to-two years of part-day educational services and home visits to 58 low-income, low-IQ African American children between the ages three and four in Ypsilanti, Michigan, during the 1960s. The program

<u>Childcare Quality</u>
Supportive Interactions
Intentional Instruction

was intensive – aside from daily educational activities, program staff made weekly afternoon visits to each family. Children who were in the program showed increased IQ, but the effects of home visits and educational services dissipated by third grade. However, at age 25, children in the program showed increased employment and decreased arrest rates (Schweinhart, 1993). The Abecederian Project was even more intensive than the Perry Preschool. Fifty-seven low-income, mostly African American children in Chapel Hill, North Carolina, received full-time center-based care from birth to age five. At age 20, children who received the program's services had IQ scores .38 standard deviations higher than children who did not receive services and were 2.5 times more likely to attend college (Campbell, Ramey, Pungello, Sparling, & Miller-Johnson, 2002). A recent meta-analysis (Duncan & Magnuson, 2013) confirmed that preschool does boost children's school readiness skills and early school achievement, but the size of the effect is smaller than suggested by Perry Preschool and Carolina Abecedarian Project, partially because Perry Preschool and Carolina Abecedarian Project were so intensive, and partially because more children now receive some form of childcare, so the bar to which preschools are now compared is higher.

Evidence for Childcare as a Mediator

To the best of my knowledge, no studies have examined childcare as a mediator between income and school readiness skills, and only one study examined quality of childcare as a mediator between income and child achievement. The study did not find a mediating effect of quality of childcare on child achievement (Guo & Mullan-Harris, 2000). However, the study had several limitations. First, the study defined quality of childcare by the staff/children ratio and teacher training. However, staff/children ratio and teacher training may not be indicative of high-quality childcare because it does not guarantee supportive interactions between children, caregivers, and teachers, nor does it guarantee intentional instruction. Second, the analyses focused on families whose children were in childcare, and thus did not compare childcare to no childcare. Finally, data collection for the sample ended in 1992. Formal childcare use has increased dramatically since 1992, and so an update to the analysis is needed.

An updated analysis may suggest that quality of childcare mediates the relation between an additional $1,000 in family income and increased school readiness skills. More recent research suggests that the 1996 Federal Welfare Reform may have encouraged parents in poverty to place their children in lower-quality home-based care, while high-income families have continued to benefit from the use of high-quality childcare (Bassok, Fitzpatrick, & Loeb, 2011; Herbst & Tekin, 2010). The 1996 Federal Welfare Reform was a series of laws passed that sought to encourage individuals receiving welfare to work more. It accomplished this goal by making welfare eligibility time-limited, and it also increased the tax credits that working families could receive. In response to the 1996 Federal Welfare Reform, low-income mothers were employed more often, and as a result placed their children in childcare. A year in childcare reduced child test scores by 2.1% of a standard deviation. Childcare effect was explained by placement in home-based care, as home-based care is often of lower quality than center-based care. In the face of encouragement and sanctions designed to increase employment, families in poverty may place their children in low-quality childcare at increasing rates because center-based childcare can be prohibitively expensive, while high-income families continue to place their children in high-quality care. This pattern suggests that childcare quality may mediate the relation between income and school readiness skills (↑ income → ↑ childcare quality → ↑ school readiness skills).

Because children are not required to be in childcare, the present dissertation conducts two sets of analyses when examining childcare as a mediator between an additional $1,000 in family income and increased school readiness skills. First, in order to keep families who do not use care in the analyses, the present dissertation uses dummy codes for each type of care available: Head Start, public preschool center, private childcare or preschool centers, home-based care, or no care at all (parental care). Research suggests that center-based care is often higher quality than home-based care (Abner, Gordon, Kaestner, Korenman, 2013; Bernal & Keane, 2011), so it is still possible to examine quality of childcare as a mediator with these dummy codes. Second, the present dissertation omits parents who do not use care and examines childcare quality across the different types of childcare. See Figure 2 for the two approaches. Given the lack of research that examines childcare as a mediator between income and school readiness skills, the third aim of the proposed dissertation is exploratory, and, as such there are no a priori hypotheses about its role as a mediator.

Control Variables

The present dissertation controls for the following variables: 1) marital status, 2) employment status, 3) number of children, 4) maternal education, 5) childcare subsidy use, and 6) maternal depression. The- control variables are used because the present dissertation examines the causal impact of an additional $1,000 on school readiness skills. Each of control variables could conceivably affect school readiness skills via changes in parenting, but they also may affect income: 1) a recently married mother may behave differently towards her child, but the marriage will also result in an increase in income; 2) a mother who enters the workforce after unemployment or part-time work has less time to spend with her children, but also earns more income; 3) a mother with more children may have less time to devote to any one child, but also has less disposable family income; 4) mothers with more education have more income than mothers with less income, and research suggests mothers with more education engage in more parenting practices that promote cognitive development (Conger & Donnellan, 2007); 5) mothers who use childcare subsidies might have more disposable income and more time to work, which might also lead to more income, but research suggests that subsidy use is associated with more negative parental child interactions, presumably because mothers who use subsidies enter stressful jobs (Baker, Gruber, & Milligan, 2005); and 6) more depressed mothers may earn less income and may also engage in fewer parenting behaviors that promote cognitive development (Conger & Donellan, 2007; Zimmerman & Katon, 2005). The present dissertation examines models that do and do not control for maternal depression because while the other control variables clearly precede additional income, it is unclear the extent to which maternal depression causes, or is the result of, less income.

Moderation

The present dissertation conducts a moderation analysis for families at different quartiles of the income distribution. There appears to be a U-shaped pattern to high-quality childcare availability and family income: high-quality care exists in areas with dense poverty as well as wealthy areas. There is less high-quality childcare in areas where the median income is in the middle of the income distribution (Bassok, Fitzpatrick, & Loeb, 2011). Mothers in the middle of the income distribution may not have the option to select higher quality providers, even if their income increases, and so mediation may not exist when examining all families together.

The present dissertation also conducts a moderation analyses for racial/ethnic group. Research suggests that different racial/ethnic groups have different patterns of childcare use (Radey & Brewster, 2007), so a moderation analysis is needed to examine whether similar patterns exist across groups. There are no a priori hypotheses for these analyses, but the results will help in examining whether the results generalize across groups.

Taking Advantage of Multiple Sources of Data

In this dissertation, two unique datasets were examined to address the hypotheses. Each dataset offers complementary information. The Study of Early Childcare and Youth Development (SECCYD) project followed children from birth to ninth grade, from 1991 to 2007. Children were recruited from hospitals located in or near Little Rock, AK; Irvine, CA; Lawrence, KS; Boston, MA; Philadelphia, PA; Pittsburgh, PA; Charlottesville, VA; Morganton, NC; Seattle, WA, and Madison, WI. The SECCYD provides detailed information on family income, childcare, parenting behaviors, and school readiness skills. Moreover, the study took place before the federal welfare reform of 1996 and the dramatic increase in childcare use. As such, the dataset can offer information on each of the proposed dissertation's aims prior to federal welfare reform and increased childcare use. The SECCYD is a relatively affluent sample – although there is a considerable range of income in the dataset, the median household income was higher than the national average at the time.

The Early Childhood Longitudinal Study – Birth Cohort (ECLS-B) is useful in that it provides a large sample size: 10,000 children (approximately 14 times as many children as there are in the SECCYD) sampled from across the country. Like the SECCYD, the ECLS-B is longitudinal – children were followed from 9 months old to kindergarten. A limitation of the ECLS-B is that it does not have as in-depth measures of parenting behaviors as the SECCYD. By examining my hypotheses in both datasets, the present dissertation can assess the generalizability of results from a single dataset.

Hypotheses

The proposed dissertation has three aims: 1) Examine the impact of an additional $1,000 in family income on school readiness skills; and 2) examine increases in cognitive stimulation, and 3) higher quality childcare as mediators of the relation between an additional $1,000 in family income and increased school readiness skills.

In respect to the first aim, the present dissertation hypothesizes that in each dataset, with each analytic technique, an additional $1,000 in family income will predict increased school readiness skills. In respect to the second aim, the present dissertation hypothesizes that in each dataset, with each analytic technique, more cognitive stimulation will mediate the relation between an additional $1,000 in family income and increased school readiness skills. In respect to the third and final aim of the dissertation, given the lack of research on childcare quality as a mediator between an additional $1,000 in family income and increased school readiness skills, there are no a priori hypotheses.

Study 1: The Study of Early Childcare and Youth Development (SECCYD)

Method

Participants

Mothers were recruited from hospitals located in or near Little Rock, AK; Irvine, CA; Lawrence, KS; Boston, MA; Philadelphia, PA; Pittsburgh, PA; Charlottesville, VA; Morganton, NC; Seattle, WA; and Madison, WI. In 1991, research staff visited 8,986 mothers giving birth in identified hospitals. Of the mothers screened, 5,416 met eligibility criteria and agreed to be contacted after returning home from the hospital. A randomly selected subgroup (with procedures to ensure economic, educational, and ethnic diversity) were contacted and enrolled in the study. The resulting sample identified 1,364 families with healthy newborns. Details of the selection procedure are published in the Manuals of Operation of the NICHD Study of Early Childcare (NICHD ECCRN, 1993).

Among the children in the original sample, 49% were female. The majority of children were White (n=1214; 89%), followed in frequency by African American (n=176), Hispanic (n=83), and Other (n=39). Maternal education ranged from seven to 21 years, with a mean of 14.45 years. The income-to-needs ratio, used to measure income relative to the number of household members, ranged from 0.12 to 33.77, with an average of 3.73; this translates to $75,197 in 2016, for a family of three. Thus, the average income-to-needs ratio of the SECCYD indicates a largely non-poverty sample, although there was a considerable range.

Overview of Data Collection

Children in the SECCYD were followed from birth through the sixth grade. Maternal education and child ethnicity were reported when children were one month old. Children's teachers in kindergarten through twelfth grade were distributed across 747 schools, in 295 public school districts, in ten states. Further description of data collection procedures, psychometric properties of measures, and descriptions of how composites were derived is documented in the Manuals of Operation of the NICHD Study of Early Childcare (NICHD ECCRN, 1993). Retention of participants was high. Of the 1,364 families that participated in the Phase I assessments (birth through 36 months), 1,226 (90%) participated in the Phase II assessments (54 months through first grade). The proposed dissertation focuses on the assessments at six months, 15 months, 36 months, and 54 months.

Measures

For a table of the measurements available at each wave, see Table 1.

Cognitive stimulation.

The present dissertation uses the Home Observation for Measurement of the Environment at the six-month, 15-month, 36-month, and 54-month assessments (H.O.M.E.; Caldwell & Bradley, 1984) to measure cognitive stimulation. The H.O.M.E. Inventory provides an overall assessment of a range of home experiences related to child behavior and development through a combination of direct observation and a semi-structured interview. The one-hour assessment (including observation) measures the stimulation and support available to the child in the home environment and contains 57 items in 8 subscales. Each item is scored using a binary (yes = 1, no = 0) scoring system. For the proposed dissertation, the following subscales were used to assess cognitive stimulation: 1) learning materials, 2) stimulation of language development and 3) academic stimulation. Sample items from the academic stimulation subscale include, “Child is encouraged to learn shapes” and “Child is encouraged to learn numbers.” Sample items from the language stimulation subscale include, “Parent teaches child simple verbal manners” and “Parent uses correct grammar and pronunciation.” Sample items from the provision of learning materials subscale include observations of whether there were toys in the home that help children learn colors and shapes. Inter-observer agreement was excellent (>90%), and alpha for the composite of the subscales was .88. Although the items of the H.O.M.E are stable over time, their meaning to children and parents change over time because children’s development affects parent-child interactions (Bell, 1979). In order to ensure that the same construct was assessed over time, the present dissertation applies an idiographic filter to the H.O.M.E, per recommendations from Dodson (2016). A more detailed description of the idiographic filter procedure is located in the Measurement and Data Analytic sections.

Childcare.

To measure childcare quality, the present dissertation uses the Observation Ratings of the Caregiving Environment (NICHD Early Child Care Research Network, 2000; ORCE). The ORCE assesses childcare quality in both home and center-based settings. Study children were observed for a total of four 44-min observation cycles at each age at the nonmaternal childcare setting in which the child spent at least 10 hours per week. At 6 and 15 months, sensitivity to child's non-distress expressions, positive regard, stimulation of cognitive development, detachment, and flat affect were assessed with observer ratings. At 36 months, two additional categories were added: fostering exploration and intrusiveness. At 54 months, ratings were focused on sensitivity and responsivity, stimulation of cognitive development, intrusiveness, and detachment. The present dissertation creates a latent factor of quality at each time point with each indicator, and uses an idiographic filter to address the changing measurement, following recommendations from Dodson (2016).

School readiness skills.

To measure school readiness skills, the present dissertation uses a variety of assessments: the Bayley Scales of Infant Development, Bracken Scale of Basic Concepts and the Woodcock-Johnson Psycho-educational Battery.

At 15 months, the Mental Development Index from the Bayley Scales of Infant Development, 2nd ed. (Bayley II; Bayley, 1993) was used to assess overall developmental status. The Bayley Scales are the most widely used measures of infant cognitive ability and have very good psychometric properties (Gagnon & Nagle, 2000).

During the 36-month home visit, children's cognitive development was assessed using the School Readiness composite from the Bracken Basic Concept Scale (Bracken, 1984). The 51-

item measure assesses children's abilities in the areas of color recognition, letter identification, number/counting skills, comparisons, and shape recognition. The School Readiness composite has demonstrated good validity via strong correlations with intelligence measures and academic performance in kindergarten (Laughlin, 1995; Zucker & Riordan, 1987). The measure has also demonstrated good split-half and test-retest reliability (Bracken, 1984). In the present sample, the internal consistency of the measure was excellent ($\alpha = .93$).

School readiness skills at the 54-month assessment were obtained using the revised version of the Woodcock-Johnson Psycho-Educational Battery (WJ-R; Woodcock & Johnson, 1989; Woodcock, 1990). The WJ-R is composed of two batteries designed to assess a child's cognitive aptitude and achievement. The presentation dissertation uses the Tests of Achievement (WJ-R ACH) to measure school readiness skills, which has shown excellent internal consistency (.94 to .98). The present dissertation forms a latent factor of school readiness skills from the subscales of the WJ-R ACH.

Income.

Parent-reported income was converted to 2016 dollars with the inflation calculator from the Bureau of Labor Statistics (Bureau of Labor Statistics, 2010).

Control variables.

Maternal depression was measured with the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977) at the six, 15, 36, and 54-month assessments. The CES-D is a self-report scale intended to measure symptoms of depression in non-clinical populations. It is one of the most widely used and validated measures of depressive symptomatology for non-clinical samples.

Maternal employment was measured with maternal-reported hours worked per week at each assessment. Maternal education was measured with maternal-reported education at baseline (1991). Categories of education ranged from high school to graduate degree. Given large number of categories and ordinal nature of education, the present dissertation treats maternal education as a continuous variable. The SECCYD did not assess childcare subsidy use, so it was omitted as a control variable.

Measurement

In order to address the changing indicators used to measure childcare quality on the ORCE and the changing meaning of the items as children age, the present dissertation uses an idiographic filter. With an idiographic filter, the indicators of a latent variable can change, but the interpretation of the latent variable remains the same. Consider the calculation of the area for a triangle (1/2 bh), circle (π R^2), and square (lw): these calculations are not comparable. But, the volume calculation is the same (V = A x S) across triangles, circles, and squares, and so A and V have the same meaning from one group to another (Nesselroade, Gerstof, Hardy, & Ram, 2007). In order to fit an idiographic filter, there must be a first and second order factor. The first order factor is the area calculation, which is free to vary across the shapes, and the second order factor is the volume calculation, which is constant across shapes. For the proposed dissertation, the first order factors are childcare quality and cognitive stimulation, and the second order factors are the change in childcare quality and cognitive stimulation.

Data Analytic Strategy

Longitudinal fixed effects.

The present dissertation uses a longitudinal fixed effects estimation strategy to estimate the impact of an additional $1,000 in family income on increased school readiness skills while examining higher childcare quality and more cognitive stimulation as mediators. In a fixed-effects regression, between-participant variability is held constant so that an unbiased estimate of within-participant variability can be obtained. With a cross-sectional analysis, the predictors are between families – i.e., children from families with more income display more school readiness skills. With longitudinal fixed effects, the comparison is within each family – how a change in income within one family relates to a change in school readiness skills within that same family. A longitudinal fixed effects approach can reduce omitted variable bias, as any stable traits within a family are removed from the analysis. For example, intelligence is relatively stable in adulthood, and so modeling the change between income and cognitive stimulation can reduce the influence of parental intelligence:

$$CogS_t = Inc_t + Int + e$$

$$CogS_{t-1} = Inc_{t-1} + Int + e$$

$$CogS_t - CogS_{t-1} = Inc_t - Inc_{t-1} + e$$

However, if within-participant variability varies over time, then a fixed effects approach will continue to give biased estimates. For example, income and maternal depression covary (Conger & Donellan, 2007; Zimmerman & Katon, 2005). If changes in maternal depression are not controlled for, the effect of an additional $1,000 in family income on school readiness skills includes the effect of income, along with the effect of maternal depression. On the other hand, if changes in maternal depression are controlled for, then the effect of income may be obscured. Because neither income nor depression is randomly assigned, it is impossible to say which approach is more appropriate. It is possible that an additional $1,000 in family income precedes decreased depression. It is equally possible that decreased depression precedes an additional $1,000 in family income. An inability to tease apart time-varying factors is clearly a limitation of the proposed dissertation, but the longitudinal fixed effects regression is still an improvement over a standard regression predicting school readiness skills from family income because variability due to constant factors is removed.

The present dissertation uses a longitudinal fixed effects model, and so models the change in the control variables (marital status, employment status, number of children, maternal education, and maternal depression). To estimate the fixed effects longitudinal model, the present dissertation creates a difference score for income, and a latent difference score for cognitive stimulation, and childcare. The SECCYD did not record type of childcare, so Study 1 does not examine change in type of childcare. The number of children for whom childcare was observed varied over the course of the study ($N_{\text{Six Months}}$ = 593; $N_{\text{15 Months}}$ = 658; $N_{\text{36 Months}}$ = 707; $N_{\text{54 Months}}$ = 854). For school readiness, the present dissertation includes an autoregressive parameter, which also captures change. The full model can be depicted with the following equation:

$$\Delta\, SR = \Delta\, Marital + \Delta\, Employment + \Delta\, Children + \Delta\, Education + \Delta\, Depression + \Delta\, Income + e$$

where SR = School Readiness Skills and Δ = change.

Latent difference score.

The present dissertation uses a latent difference score because it eliminates reversion to the mean as a source of bias. A potential issue with a within-participant comparison is reversion to the mean – children that experience a large drop in school readiness skills are bound to revert to their mean, even if family income does not change, potentially attenuating the impact of income on school readiness; the same is true for parenting and childcare. The reversion to the mean is compounded by measurement error. In order to protect against reversion to the mean due to measurement error, the present dissertation uses a Latent Difference Score. Latent Difference Score models are defined by the following equation:

$$Y_t = (1)Y_{t-1} + (1)\Delta Y_t$$

Thus, the true score of a construct at a given time point, Y*t*, is the sum of the construct at the prior time point (Yt-1) plus the unobserved true change in the construct (deltaY) at time point *t*. According to the equation, the difference score is proportional to the gain in the true score and the random error. In order to isolate the true score, multiple measurements of the same construct within occasion can be used, as depicted in Figure 5. Importantly, the constructed latent factor does not include measurement error, and so bias from measurement error creating regression to the mean is no longer an issue (McArdle & Nesselroade 1994, Nesselroade, Stigler, & Baltes, 1980).

In contrast to cognitive stimulation and childcare quality, there is only one indicator of income, which may contain measurement error. Following recommendations from Westfall and Yarkoni (2016), the loadings of income were fixed to 1.0 and the variances of its residuals were fixed to $(1 - \alpha)s^2$, where α_j is the assumed reliability of the income – for which a range of values was entered – and s^2 is the sample variance of income. The Westfall and Yarkoni approach assesses the stability of the results by demonstrating how robust findings are to poor measurement.

Idiographic filter.

In sum, change in income was modeled by a difference score, change in childcare quality and cognitive stimulation was measured by a latent difference score, and change in school readiness skills was modeled by an autoregressive parameter. See Figure 6 for a more detailed depiction of the model, focused at two waves, for ease of interpretation. To fit the idiographic filter, the steps outlined below were followed for cognitive stimulation and for childcare quality. Model fit was examined at each step via Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Standardized Root Mean Square Residual (SRMR). A worsening model fit indicates that the second order factor (change) is not stable over time.

1. First, a latent variable of each construct at each time point (first order factors) was created.
2. Next, for each latent variable, the first order factor variances were fixed to be equal over time, so that the first order factors are on the same scale. See Figure 7.
3. Then the autoregressive parameters were fixed to be equal over time. As with areas and volumes, this step tests whether the relation within the construct is stable over time. See Figure 8.

4. Finally, the regression parameter of maternal education onto each latent was constrained. This step provides an additional test for whether the relation between the latent variable and an additional construct is stable over time.

Study 1: Results

Please see Table 4 for means, standard deviations, and correlations.

Results are presented in the following order: 1) latent variable creation and idiographic filter, and 2) model results. Model results are presented in the following order: 1) School Readiness Skills, 2) Cognitive Stimulation, 3) Childcare Quality and 4) Mediation. This same order is repeated for moderation analyses with 1) income quartiles and 2) race/ethnicity. All analyses were conducted in lavaan (Rosseel, 2011), using Full Information Maximum Likelihood and robust standard errors.

Latent Variables

Cognitive stimulation.

At the 6 and 15-month assessments, the present dissertation forms a latent variable of cognitive stimulation from the following indicators: 1) learning materials, 2) involvement, 3) responsiveness and organization. At 6 months, the model showed excellent fit (RMSEA = .078, CFI = .995, TLI = .986, SRMR = .01), and also at 15 months (RMSEA = .07, CFI = 1.00, TLI = .99, SRMR = .01). At the 36 and 54 month assessments, the present dissertation forms a latent variable of cognitive stimulation from the following indicators: 1) learning materials, 2) academic stimulation, and 3) language stimulation. Both of these models had perfect fit.

The present dissertation then put each of these latent variables into a single model, added an autoregressive parameter to each, and regressed maternal education onto each. The model showed acceptable fit (RMSEA = .07, CFI = .92, TLI = .90, SRMR = .07). Fixing the variance of each latent variable to be equal substantially worsened model fit (RMSEA = .10, CFI

= .84, TLI = .81, SRMR = .15). Model fit did not worsen when the autoregressive parameters were constrained to be equal (RMSEA = .10, CFI = .84, TLI = .81, SRMR = .15), or when the effect of maternal education was constrained to be equal (RMSEA = .10, CFI = .83, TLI = .81, SRMR = .15). The application of the idiographic filter suggests that cognitive stimulation was not stable over time, as cognitive stimulation was not on the same scale at each wave – fixing the variance of the latent variable worsened model fit. Results from the latent difference score should not be interpreted as change in cognitive stimulation, but rather cognitive stimulation at time t, controlling for cognitive stimulation at $t - 1$.

Childcare quality.

At the 6 and 15-month assessments, the present dissertations formed latent variable of childcare quality from the following indicators: 1) sensitivity to distress, 2) sensitivity to non-distress, 3) intrusiveness, 4) detachment, 5) stimulation, 6) positive regard, and 7) flat affect. At 6 months, the model showed acceptable fit (RMSEA = .12, CFI = .95, TLI = .92, SRMR = .04), and also at 15 months (RMSEA = .11, CFI = .95, TLI = .92, SRMR = .04). At the 36-month assessment, the present dissertation formed a latent variable of childcare quality from the following indicators: 1) fostering exploration, 2) sensitivity to non-distress, 3) intrusiveness, detachment, 4) stimulation of development, 5) positive regard, and 6) flat affect. The model showed acceptable fit (RMSEA = .10, CFI = .95, TLI = .92, SRMR = .04). At the 54-month assessment, the present dissertation forms a latent variable of childcare quality from the following indicators: 1) intrusiveness, 2) detachment, and 3) stimulation. The model showed perfect fit.

Next, each of the latent variables was put into a single model, an autoregressive parameter was added to each latent variable, and maternal education was regressed onto each latent variable. The model showed acceptable fit (RMSEA = .04, CFI = .91, TLI = .90, SRMR = .06). Fixing the variance of each latent variable to be equal slightly worsened model fit (RMSEA = .05, CFI = .90, TLI = .88, SRMR = .07). Model fit worsened further when the autoregressive parameters were constrained to be equal (RMSEA = .05, CFI = .88, TLI = .87, SRMR = .11), but did not worsen when the effect of maternal education was constrained to be equal (RMSEA = .05, CFI = .88, TLI = .87, SRMR = .11). The application of the idiographic filter suggests that the childcare quality was not stable over time because it did not share a consistent relation within itself. Results from the latent difference score should not be interpreted as change in childcare quality, but rather childcare quality at time t, controlling for childcare quality at $t - 1$.

Main Effects

School readiness skills.

The model showed good fit (RMSEA = .04, CFI = .92, TLI = .90). An examination of the residual correlation matrix showed that the Memory for Sentences and Incomplete Words Score indicators of the Woodcock-Johnson showed a large residual correlation ($r = .14$). Estimating a covariance between these two items substantially improved model fit (RMSEA = .03 CFI = .95, TLI = .94).

Results indicated that change in income from six to 15 months predicted a .01 SD unit decrease in the Bayley Mental Development Index, although the effect was not statistically reliable ($p = .099$). Change in income from the 15 to 36-month assessment predicted a .01 SD unit increase in the Bracken Basic Concept Scale, but the effect was not statistically reliable ($p = .057$). Change in income from 36 to 54 months did not predict scores on the Woodcock-Johnson at the 54-month assessment ($p > .05$). Adding change in maternal depression in each regression did not alter the results.

Cognitive stimulation.

The model showed poor fit (RMSEA = .06, CFI = .80, TLI = .78). An examination of the residual correlation matrix revealed that items that were repeated over waves shared a large residual correlation ($r > .1$), and items from the first two waves shared a large residual correlation with maternal education ($r > .1$). The covariance between items that were the same over waves, as well as the covariance between maternal education and items from the first two waves were then estimated. The subsequent model showed poor fit (RMSEA = .05, CFI = .88, TLI = .86). Change in income did not predict change in cognitive stimulation at any wave ($p >$ .05).

Childcare quality.

The model showed poor fit (RMSEA = .03, CFI = .89, TLI = .88, SRMR = .05). Results indicated that change in income did not predict change in childcare quality at any wave ($p >$ .05).

Mediation.

Mediation was not tested because change in income did not predict change in school readiness skills at any wave.

Summary.

Results indicated that income did not reliably predict children's school readiness skills, parents' cognitive stimulation, or childcare quality. The stability of the effect of income was not tested, because income had no effect on any of the outcome measures.

Moderation: Income Quartiles

School Readiness Skills.

For families in the second highest income quartile, a $1,000 increase in income from the sixth to 15-month assessment predicted a .02 SD unit decrease in the Bayley Mental Development Index at the 15-month assessment ($\beta = .02$, $p = .008$). There was no evidence of moderation for any other income quartile.

Cognitive stimulation and childcare quality.

There was no evidence that income quartile moderated the relation between changes in income and changes in cognitive stimulation or the relation between changes in income and childcare quality ($p > .05$).

Summary.

Results indicated a small effect of income for families in the second highest income quartile on the Bayley Mental Development Index. However, income did not predict Bayley Mental Development scores for any other income quartile, and there was no effect on school readiness skills measured at any other wave. In addition, there was no evidence of a moderating effect of income quartile on cognitive stimulation or childcare quality. Again, the stability of the effect of income was not tested because there was limited evidence that income had an effect on outcome measures.

Moderation: Race/Ethnicity

School readiness skills.

Results indicated that relative to White families, for whom there was no effect of income on Woodcock-Johnson scores, a $1,000 increase in Hispanic families' income from the 36 to 54-month assessments was associated with a .04 SD unit increase in Woodcock-Johnson scores ($p = .002$). There not a statistically reliable difference in cognitive stimulation for any other race/ethnicity ($p > .05$). The relation between income and school readiness skills was not moderated by race at any other time point.

Cognitive stimulation.

Results indicated that relative to White families, for whom there was no effect of income on cognitive stimulation, a $1,000 increase in Hispanic families' income from the six to 15-month assessment was associated with a .10 SD unit decrease in cognitive stimulation ($p = .009$). In addition, relative to White families, for whom there was no effect of income on cognitive stimulation, a $1,000 increase in Hispanic families' income from the 15 to 36-month assessment was associated with a .03 SD unit decrease in cognitive stimulation ($p = .006$). There was not a statistically reliable difference in cognitive stimulation for any other race/ethnicity ($p > .05$). The relation between income and cognitive stimulation was not moderated by race at any other time point.

Childcare quality.

Results indicated that race did not moderate the relation between income and childcare quality (*p* > .05).

Summary.

Results again did not show a consistent effect of moderation on school readiness skills or cognitive stimulation. Results did show that an increase in income was associated with an increase in school readiness skills from the 36 to 54-month assessments for Hispanic families, and *decrease* in cognitive stimulation for Hispanic families from the six to 15-month and 15 to 36-month assessments. The stability of the effect of income was not tested because there was limited evidence of an effect of income on school readiness skills.

Study 2: Early Child Longitudinal Study – Birth Cohort

Two separate analyses on the ECSL-B were performed, but the measures in each analysis are the same. In the following section, the participants in the overall sample, the measures, and the general analysis strategy are presented. Then, the specific analysis strategy for each analysis and the participants for each analysis are presented.

Method

Participants

The ECLS-B is a nationally representative sample of approximately 14,000 children born in the U.S. in 2001. The children participating in the study came from diverse socioeconomic and racial/ethnic backgrounds with oversamples of Chinese children, other Asian and Pacific Islander children, American Indian and Alaska Native children, twins, and children born with low and very low birth weight.

Children were followed from birth through kindergarten entry. Information about these children was collected when they were approximately nine months old (2001-02), two years old (2003-04), and four years old/preschool age (2005-06). Additionally, in the fall of 2006, data were collected from all participating sample children who were in kindergarten, approximately 75 percent of the sample. In the fall of 2007, data were collected from the approximately 25 percent of participating sample children who had not yet entered kindergarten or higher in the previous collection, as well as children who were repeating kindergarten in the 2007-08 school year. See Tables 5 and 6 for participant characteristics at each wave, and see Tables 8 and 9 for participant characteristic in the childcare sample.

Measures

For a table of the measurements available at each wave, see Table 3.

Childcare.

For cost reasons, the ECLS-B observed childcare quality for a randomly chosen 25% subsample of the children whose parents reported using non-parental care for at least 10 hours per week. This group is referred to as the Childcare Observation (CCO) sample. Children who lived in Alaska, Hawaii, resided in American Indian supplement Population Sampling Units, or in a care setting where the language spoken was one other than English or Spanish were not eligible for observation and thus not included in childcare sample, which amounted to a total of 500 children. All eligible cases where the child lived in poverty and spent the most hours per week in a center-based care arrangement were included in the CCO sample with certainty. All other eligible cases were subsampled at rates designed to reduce the variability in probabilities of selection resulting from the oversampling of low and very low birth weight children in the base ECLS-B sample.

For children in center-based care, ECLS-B observers rated the quality of care using The Infant/Toddler Environment Rating Scale (ITERS) and for children in home-based care, observers rated childcare quality using the Family Day Care Rating Scale (FDCRS) (Harms, Cryer, Clifford, 1990). ITERS is a classroom-level measure of childcare quality that examines the child's experiences in the care setting. The ITERS examines interactions with adults and peers, exposure to materials and activities, whether routine care needs are met, and the furnishings and displays in the classroom. Harms, Cryer, and Clifford (1990) reported inter-rater and test–retest reliability of r = 0.58 and r = 0.89, respectively, and internal consistency of α = 0.83. The present dissertation uses the quality score on the ITERS (α = .86 in the ECLS-B). This score contains 29 items from the broad categories mentioned above and is on a 7-point scale.

The FDCRS measures the same experiences as the ITERS: interactions with adults and peers, materials and activities exposure, whether, how much, and the manner in which routine care needs are met, and classroom furnishings and displays (9-month to 2-year User's Manual). Inter-rater reliability for the FDCRS was reported to be r = .90, internal consistency was only reported for the subscales and varied from α = 0.7 to α = .93. The original manual did not report on concurrent validity, but other studies report high correlations (.80) between the FDCRS and visitors' ratings of family day care settings (US Administration for Children and Families, 2013). The present dissertation uses the total quality score on the FDCRS (α = .88 in the ECLS-B), which contains 33 items drawn from the categories mentioned above and is also on a 7-point scale.

ECLS-B staffers who rated the quality of care for study children received an extensive multi-day training. To be certified on either the ITERS or FDCRS, observers were required to have 80% of their scores within one point of the consensus score as well as a positive trainer evaluation.

To measure childcare quality, the present dissertation borrows from prior research (Burchinal & Nelson, 2000; Ruzek, Burchinal, Farkas, & Duncan, 2014) that treats scores from each measure equally in analyses and accounts for potential differences in mean scores and variability across the two instruments. To ensure the quality construct is appropriate, the present dissertation allows quality to vary by type of care to account for any differences that might be measure based.

Childcare Type

Parents were asked to report the type of childcare their children attended. Possible responses were parental care, relative care in child's home, relative care in another home, relative care varied location, nonrelative care in child's home, nonrelative care in another home, nonrelative are varied location, center-based program, Head Start, and location varies. The different relative and nonrelative care options were binned into a single other care option, while center-based and Head Start were kept as separate indicators. Families who reported multiple arrangements were grouped together with parental care.

Cognitive stimulation.

The present dissertation assesses cognitive stimulation via the maternal reported book reading item from Home Observation for Measurement of the Environment – Short Form (HOME-SF). The present dissertation focuses on the item that assesses book reading because book reading is particularly important in children's cognitive development (Mayer, Kalil, Oreopoulos, & Gallegos, 2015), and research suggests that it shares a strong relation to family income (Portnow & Hussain, 2016).

School readiness skills.

The present dissertation uses a variety of instruments to assess children's school readiness skills. At nine and 24 months, the present dissertation uses the mental scale of the Bayley Short Form-Research Edition (BSF-R). The BSF-R was developed specifically for the ECLS-B and includes a subset of questions from the larger Bayley Scales of Infant Development – Second Edition (BSID-II). The BSF-R mental scale measures a child's performance on tasks requiring memory, problem-solving, and language skills. Children were presented tasks, such as naming pictures, verbal comprehension, comparing sizes, and matching colors. ECLS-B staffers who administered the BSF-R received a 3-day intensive training on administering and scoring the individual BSF-R items, which culminated in each staffer administering a live BSF-R to a 21 to 30-month old child to ensure and measure accuracy. Staffers who ended up administering the BSF-R as part of the full data collection effort scored an average of 93 percent for administration accuracy and an average of 97 percent for scoring accuracy on the BSF-R mental scale. The scale scores were calculated using Item Response Theory (IRT) true-score equating so that BSF-R scores were on the same scale as the BSID-II. The observed overall BSF-R mental scale reliability coefficient was 0.975.

Kindergarten reading and math skills were measured at preschool and kindergarten using direct assessments that drew items from well-validated standardized instruments, such as the Preschool Comprehensive Test of Phonological and Print Processing (Pre-CTOPPP), Peabody Picture Vocabulary Test (PPVT), the PreLAS 2000, and the Test of Early Mathematics Ability-3 (TEMA-3). Additionally, items were borrowed from the Family and Child Experiences Study (FACES) and ECLS-K. The reading assessment evaluated early language and literacy skills like letter-sound knowledge, print conventions, word recognition, expressive and receptive vocabulary, interpreting text, and critical reading. The mathematics assessment evaluated skills such as number sense, properties, operations, measurement, geometry, spatial sense, data analysis, and patterns. Responses to these items were formed into latent traits of reading and math skills via IRT by the ECLS-B staff.

Income.

Parent-reported income was transformed each year to reflect 2016 dollars.

Benefits.

Benefits were computed with TAXSIM, a tax calculator published through the National Bureau of Economic Research (NBER; Feenberg & Coutts, 1993).

Control variables.

Maternal depression was measured with the Center for Epidemiological Studies Depression Scale (CES-D; Radloff, 1977) at the nine-month, four-year, and kindergarten assessments, but was not measured at the two-year assessment.

Maternal employment was measured with maternal-reported hours worked per week at each assessment. Maternal education was measured with maternal-reported education at each assessment. Childcare subsidy use was computed from information provided by parents, child care providers, and child care directors at the 2-year, pre-k, and kindergarten assessments, following a procedure outlined by Johnson, Martin, & Brooks-Gunn (2013).

Data Analysis Plan

A standard ordinary least square regression of the relation between income and school readiness skills produces a biased estimate of the effect of income because of omitted variable bias: children from more economically disadvantaged families display lower school readiness skills than their economically advantaged peers, but their parents often have less education, live in more dangerous neighborhoods, and have access to worse schools, among many other disadvantages. It is impossible to control for all of these disadvantages in any one analysis, and so a standard ordinary least squares regression cannot provide information on the impact of additional income on school readiness skills. More specifically, the error of the regression predicting school readiness schools from income is correlated with the income – violating a central assumption of ordinary least square regression. Income is correlated with the error term because income is correlated with multitude of disadvantages not controlled for.

To examine the impact of income on school readiness skills, the present dissertation uses an instrumental variable strategy. An instrumental variables strategy removes the influence of omitted variables by leveraging variation in an exogenous predictor of a treatment (i.e., income) to isolate the impact of the treatment that comes through that exogenous variation. In the case of the presentation dissertation, instrumental variables estimation isolates the portion of the variance in income that is due to exogenous variation, thereby removing the correlation between income and the error of the relation between income and school readiness skills. The steps of instrumental variable estimation are as follows: 1) predict the treatment (i.e., an additional $1,000 in family income) from an exogenous predictor of the treatment, 2) extract these predicted values of the treatment and 3) use these predicted values of the treatment to predict the outcome (i.e. school readiness skills). Instrumental variables require four assumptions:

1. Ignorability of the instrument. This assumption dictates that the instrument must be explicitly randomly assigned by a researcher, or the instrument must be ignorably assigned (i.e., the participant characteristics do not interact with the assignment of the instrument).
2. Nonzero association between instrument and treatment variable assumes that the instrument must affect the treatment.
3. Monotonicity dictates that there are no participants who would refuse the treatment if it were offered, but would take the treatment if it were not offered.
4. Exclusion restriction prescribes that the instrument affects the outcomes *through the treatment*.

An example: Sesame Street.

Consider that a research team wants to know the effect of watching Sesame Street on letter recognition (Gelman & Hill, 2007). Knowing that they cannot force children to watch Sesame Street, the research team randomly assigns families to encourage their children to watch Sesame Street, or to not encourage their children to watch Sesame Street. To their dismay, some children who were encouraged to watch Sesame Street never did, while others who were not encouraged to watch Sesame Street did watch Sesame Street. The research team cannot run a regression on assignment status to determine the effect of Sesame Street on letter recognition, as this analysis lumps together children who did not do as their parents told them with children who did as their parents told them. Rather, they must use instrumental variables. The instrumental variables approach will tell the research team what the effect of watching Sesame Street is on letter recognition, *for the children who complied with the encouragement*. A mathematical derivation of the strategy is as follows:

$$y = B_0 + B_1 T + B_2 Z + error,$$

where y = letter recognition, B_0 = intercept, B_1 = effect of watching Sesame Street and B_2 = effect of randomization of encouragement.

In an instrumental variables strategy, the predicted values of treatment are used, instead of the actual treatment. Thus,

$$y = B_0 + B_1(\gamma_0 + \gamma_1 z) + B_2 z + error,$$

where γ_0 = intercept of watching Sesame Street, and γ_1= effect of randomization of encouragement on watching Sesame Street. B_1 thus represents the coefficient for the values of treatment that are predicted from a regression of random assignment on watching Sesame Street.

Multiplying terms, the equation becomes:

$$y = B_0 + B_1\gamma_0 + (B_1\gamma + B_2)z + error$$

Note that in terms of a mediation model, the terms in the parentheses are the total effect (the indirect effect plus the direct effect). β_2 is the effect of randomization, and $B_1\gamma_1$ is the effect of watching Sesame Street multiplied by effect of randomization of encouragement on watching Sesame Street. Separating intercepts from slopes, the equation is:

$$y = \delta_0 + \delta_1 z + error$$

From this equation, we want to solve for δ_1, the total effect (the indirect effect plus the direct effect). Fortunately, the total effect can be obtained by predicting letter recognition from randomization of encouragement; as in a mediation framework, omitting the mediating variable simply pushes the variance into the predictor. After solving for the total effect, then we can solve for B_1, the unbiased treatment effect.

$$\delta_1 = B_1\gamma_1 + \beta_2,$$

which we can rearrange to get

$$\beta_1 = (\delta_1 - B_2)/\gamma_1$$

From the exclusion restriction, we know that B_2 is 0, so

$$\beta_1 = \delta_1/\gamma_1$$

Thus, the unbiased treatment effect is the effect of randomization on letter recognition divided by the effect of the randomization on encouragement. In other words, the unbiased treatment effect is the effect of watching Sesame Street *for the children who complied with the randomly assigned encouragement* – children who watch Sesame Street when their parents encouraged them are compared to children who did not watch Sesame Street when their parents did not encourage them to watch.

Study 2a: Instrumental Variables – Benefits Increases

The present dissertation uses two separate instruments to get an unbiased estimate of income. For the first instrument, the present dissertation uses random variation in the State Earned Income Tax Credit (SEITC) between states over time, as well as variation over time in the Additional Child Tax Credit (ACTC). The present dissertation considers benefits as a proxy for family income. As long as take-up of benefits is high, then benefits represent an addition to family income. The State Earned Income Tax Credit is a percentage of the federal EITC that some states allow families to claim, in addition to federal EITC. These states vary over time and according to the number of children in how much additional EITC families can claim. The ACTC is a refundable tax credit for families with dependent children. In Wave 1, families could receive a credit equal to 15% of their earnings, up to a maximum of $500 per child. In 2003 (Wave 2 of the ECSL-B), the maximum allowable additional child tax credit was doubled to $1,000 per child. As such, the ACTC also varies over time. Variation in the SEITC and the ACTC gives an unbiased estimate of a proxy for family income – an increase in benefits.

In order to obtain variation in benefits, the present dissertation uses a procedure outlined by Milligan and Stable (2012). The procedure was follows: 1) use TAXSIM, a tax calculator (Feenberg & Coutts, 1993), and the March Supplement of the Current Population Survey, to generate a random sample of benefits in the United States; 2) aggregate these simulated benefits up to the state-year-number of children cell level and merge the cells into the ECLS-B; 3) calculate the maximum eligible child benefits for each family in the sample using all available family characteristics with TAXSIM; and 4) instrument for maximum eligible benefits using simulated cells merged from TAXSIM. While the ECLS-B contains detailed information on children and families, it lacks detailed income information, and as such, cannot provide accurate information for aggregated simulated benefits. As outlined by Milligan and Stable (2012), the present dissertation uses a second dataset, the March Supplement of the U.S. census from which to generate a random sample of benefits in the United States. The present dissertation randomly samples 3,000 families from 2000-2010 2,000 times, calculates their maximum eligible SEITC and ACTC with TAXSIM, and aggregates the simulated benefits up to the state-year-number of children cell level and merge the cells into the ECLS-B.

A mathematical representation of this approach is as follows:

$$\text{BEN}_{tiks} = \beta_0 + \beta_1 \text{X}_{tiks} + \beta_2 \text{SIMBEN}_{tks} + \varepsilon_{tiks} \quad (1)$$

where the indices on the variables represent state (s), time (time), number of children (k), and families (i). The vector X contains controls that include time, state, number of children, maternal education, hours worked, marital status, and the second order interactions between state, time, and number of children. This approach also controls for differences in benefits between states over time, differences in benefits for different numbers of children over time, and differences between states in how generous their benefits are for different numbers of children. The identification of child benefits comes from omitting the three-way interaction between state, time, and number of children. The equation used to predict outcomes is as follows:

$$\text{Outcome}_{tiks} = \alpha_0 + \alpha_1 \text{X}_{tiks} + \alpha_2 BEN_{tiks} + \eta_{tiks}. \quad (2)$$

Where the indexes on the variables represent states (s), time (t), number of children (k), and families (i). Again, the vector X contains controls that include year, state, number of children, maternal education, hours worked, and marital status, as well as the second order interactions between state, years, and number of children. BEN is the predicted value of maximum eligible benefits based on Equation 1. In practice, because many families in the ECLS-B report their income *before* they receive their tax credit, outcomes are measured at $t + 1$.

An important limitation with this approach is that maximum eligible benefits are not observed; they are inferred from TAXSIM. This approach is justifiable for families who receive EITC and ACTC – the national take-up rate for EITC is 80%, and take-up of the child tax credit is extremely high (97%; Feldman, Katuscak, & Kawano, 2016). To my knowledge, there is no research that examines take-up of the additional child tax credit, and it is possible that families could claim another credit that might reduce their refundable additional child tax credit. However, it is unlikely that families who owed little-to-no income tax would claim another credit that would reduce the refundable additional child tax credit.

The instrumental variable approach has its drawbacks – it limits causal inference to the portion of the population that complies with treatment. However, in examining the impact of an additional $1,000 on school readiness skills, it is a particularly useful approach. Family income fluctuates for a wide variety of reasons: one parent might get promoted while another works fewer hours and subsequently earns less to care for an ailing family member. These fluctuations are not randomly assigned, and so are not of interest to the present dissertation. The instrumental variables strategy provides an estimate of the effect of variation in benefits, for families who complied with the variation. In other words, the estimates provided can be interpreted as the impact of an additional $1,000 in benefits, for families whose additional benefits came from an unexpected (to them) increase in benefits – families who received more benefits when benefits were higher are compared to families who received less benefits when benefits were lower.

Variation in benefits represents an instrument that satisfies the four assumptions of an instrumental variables estimation strategy. *Ignorability of the instrument*. In order for this assumption to be violated, participants would have to interact with the policy change. It is possible that generosity in benefits represents differences between the residents of states; however, there appears to be enough variation in benefits between similar states and over time to rule out this possibility. For example, Figure 10 shows an increase of almost 10 percentage points in the District of Columbia in just one year, while nearby Delaware did not offer EITC until 2006. Moreover, three neighboring states, Massachusetts, Vermont, and New Hampshire, have different EITC policies. Massachusetts provides about half as much EITC as Vermont, which allows families to claim 33% of the federally awarded EITC. In contrast, New Hampshire does not award EITC payments.

In addition, in 2001, the Economic Growth and Tax Relief Reconciliation Act of 2001 (EGTRRA) set a graduated schedule of the maximum ACTC from $500 beginning in 2001 to $1,000 in 2010, but The Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA) increased the amount to $1,000 onward. It is unlikely that families were able to prepare for such a rapid and unexpected increase in the additional child tax credit. It is possible that participants have more children in order to receive more benefits, but there is not much evidence to support this possibility (Hoynes, 1996). *Nonzero association between instrument and treatment variable*. Research suggests that variation in EITC shows a non-zero relation with a $1,000 increase in family income (Dahl & Lochner, 2012). The present dissertation tests this assumption via recommendations by Staiger and Stock (1994). *Monotonicity*. It is extremely unlikely that there are people who would refuse additional benefits if they were offered but would accept them if they were not offered, which satisfies the monotonicity assumption. *Exclusion restriction*. For this assumption to be violated, school readiness skills would have to be affected by variation in benefits through avenues other than increased benefits. While it is possible that an increase in benefits could affect later choices of parents, and those choices may in turn affect later school readiness skills, those choices would still be caused by the increase in benefits. As such, it is unlikely that an increase in benefits affects school readiness skills through a pathway that does not begin with an increase in benefits.

Study 2a: Participants

The ECLS-B did not collect income information on all participants: according to the manual, interviewers only asked families in or near the poverty line their exact income information (although in practice, some families far from poverty line also report their exact income). Everyone else in the sample chose their income from a range of values that spanned from 0$ to $250,000 in $5,000 increments from $0 to $50,000, $10,000 increments from $60,000 to$100,000, and $25,000 increments from $125,000 to $300,000. The present dissertation focuses its analyses on families, but in order to minimize error in obtaining an estimate for benefits, the present dissertation takes the mean of benefits computed from the low and high ranges of families reported ranges. In addition, the present dissertation controls for whether or not parents reported their exact wages.

Study 2a: Results

Please see Tables 12 through 16 for means, standard deviations, and correlations among all predictor variables at each wave, and see Tables 17 and 18 for means, standard deviations, and correlations among the childcare sample. Not depicted in the tables is the average SEITC for families who received some SEITC. Families who received SEITC received, on average, $378 (SD = $378) at Wave 1, $399 (SD = $450) at Wave 2, $390 (SD = $446) at Wave 3, $350 (SD = 416) at Wave 4, and $367 (SD = $442) at Wave 5. The maximum amount of SEITC at each wave was $1,939 at Wave 1, $3,744 at Wave 2, $3,726 at Wave 3, $3,500 at Wave 4, and $3,471 at Wave 5. Of note, the sample of families who received SEITC is small. 1,596 families received some SEITC, 207 received SEITC greater than $1,000, 9 received SEITC greater than 2,000, and only 6 families received SEITC greater than $3,000.

Data analysis of Study 2a is presented in the following order: 1) sample examination 2) nesting structure examination, 3) the strength of the instrument examination, and 4) model results. All analyses were performed with lme4 (Bates, Maechler, Bolker, & Walker, 2014).

Sample Examination

Before model building, the relation between the average SEITC available participant characteristics that were used as control variables was examined. Results indicated that minimum wage increases did not share a relation with education, marital status, subsidy use, hours worked, or race/ethnicity, which suggests that participants in states and years where the SEITC was raised were comparable to those in states and years where the average SEITC was not raised ($t < 1.96$).

Nesting Structure

In the ECLS-B there are two potential levels of nesting: time nested within families, and families within states. Without accounting for the nested structure of the data, standard errors may be incorrect because such an analysis does not allow for similarities in benefits and school readiness skills within families. Although econometricians often use fixed effects, the present dissertation uses a random effects structure to account for time nested within participants. In the ECLS-B, families came in and out of the estimation sample (BACK UP). Random effect modeling has the added benefit of partial pooling (Gelman & Hill, 2006) – families with more information are given greater weight in the analysis. In contrast, a fixed effects approach treats all families equally, which can lead to poor estimation for families with limited information.

To decide on the optimal nesting structure, the need for inclusion of random intercepts was explored by examining the amount of clustering that exists at the family level via the intra-class correlation coefficient (ICC). Then, the need for random slopes was examined by inspecting the Aikake Information Criterion (AIC). A difference in AIC of four indicates better model fit, where a lower value indicates improved fit. According to the ICC, 41% of the variance in benefits was attributable to similarity in benefits within families. An additional 6.66% of the variance was attributable to similarity in benefits within states, but state was modeled as a fixed, instead of random, effect. Allowing the effect of time to vary within families improved model fit, but inspection of the correlation among the random effects indicated a perfect correlation between the intercept of benefits and the effect of time, suggesting model overfit. The effect of time was then removed from the random effects structure. The final nesting structure can be depicted as follows:

$$Benefits_{ti} = \beta 0_{ti} + r_{ti}$$

$$\beta 0_{ti} = \gamma_{0i} + \mu_i$$

where i = individuals and t = time, γ_{0i} = average benefit for family i, and μ_i = error for family i. The control variables included in the equation were as follows: 1) assessment wave, 2) subsidy use, 3) child race, 4) child sex, 5) child age, 6) marital status, 7) dependent children, 8) education, 9) state, 10) hours worked, and 11) the second order interactions between state, time, and dependent children. The final model, with all controls, corresponds to the following model:

$$Benefits_{tis} = \beta 0_{tis} + \beta 1X_{tis} + \beta 2SIMBEN_{ts} + r_{tis} \text{ (Step 1)}$$

$$\beta 0_{tis} = \gamma_{0i} + \mu_i$$

$$School\ Readiness_{tis} = \beta 0_{tis} + \beta 1X_{tis} + \beta 2BEN_{tis} + r_{tis} \text{ (Step 2)}$$

$$\beta 0_{tis} = \gamma_{0i} + \mu_i$$

where i = individuals, t = time, and s = state. The vector X contains all control variables.

Strength of Instrument

The strength of the instruments was examined by comparing model fit via a Wald test, adjusting for clustered standard errors at the family level. As a general rule of thumb, an F value greater than 10 provides evidence that the instrument is a sufficiently strong predictor of the endogenous predictor (i.e., benefits) (Staiger & Stock, 1994).

The present dissertation performs separate models on the Bayley Mental Development Index and the math and reading skills. These separate analyses pose potential problems for the instrumental variables estimation: change in the ACTC was only evident from Wave 1 to Wave 2. In the present dissertation, treatment group families are families who received more benefits when benefits were higher. Treatment group families are compared to the control group –

families who received fewer benefits when benefits were lower. Reading and math skills were assessed at Waves 3, 4, 5. The ACTC only changed from Wave 1 to Wave 2, and so using it as an instrument at Waves 2, 3, 4, when predicting school readiness skills measured at t + 1, compares families who were not eligible for benefits to families who were, which is essentially the same as comparing the school readiness skills of low-income to high-income families – the issue the present dissertation sought to avoid!

To obtain an appropriate control group, the present dissertation omits the additional child tax credit as instrument, and instead focuses on the SEITC. With this approach, it is possible to use the SEITC as an instrument for benefits when predicting Bayley Mental Development Index, and again as instrument for benefits when predicting the math and reading skills. Moreover, this approach provides a simple control group: families in states and years with less SEITC.

In order to more accurately compare families in states and years with and without SEITC, the present dissertation adds an additional control: family income range, which was reported for all families. Without family income as a control, families who receive more benefits are compared to families who receive less. The latter group includes *both* families in states with less SEITC and families who make too much money to qualify for SEITC. With income as a control, the effect of income is removed, so the control group no longer includes families who make too much money to qualify for SEITC, resulting in a much more specific test – the treatment group is families who receive SEITC, and the control group is families who made the same income, but live in a different state. The key difference between estimating the effect of benefits on school readiness skills in a regression and instrumental variables framework is who receives more weight in the analysis. In an instrumental variables analysis, Family A, who consistently received the maximum amount of benefits, regardless of the increase, is underweighted relative to Family B, who received less benefits when the average benefit increased, or more benefits when average benefit decreased because instrumental variables equates to the ITT effect divided by the compliance rate, and Family B has a lower proportion of compliance. As such, the instrumental variables approach helps to remove the influence of families who may attempt to maximize their SEITC payment. However, SEITC follows a non-linear trajectory and as such is difficult for families to anticipate. Moreover, a family that receives less SEITC still receives more overall income, which provides incentive to not attempt to always receive the maximum amount of SEITC. As such, the instrumental variable approach will most likely be consistent with the regression that controls for income levels.

Past Wave 2, average SEITC was not a strong predictor of SEITC ($F(1, 22{,}934) = 2.296$, $p = .133$), and prior to Wave 3, average SEITC was similarly not a strong predictor of SEITC ($F(1, 17{,}956) = .692$). Given that average SEITC did not appear to be a strong predictor of SEITC, the present dissertation does not estimate an instrumental variables approach, and instead conducts an ordinary least squares regression. While it is possible that families in states and years with SEITC may purposefully reduce their income to qualify for the maximum amount of SEITC, SEITC co-occurs with EITC. If families do indeed attempt to maximize their SEITC payments, similar who try to maximize their EITC payments most likely exist in the rest of the states of the sample, which suggests that control and treatment groups most likely do not differ in any systematic way. The present dissertation tests of differences in predictor variables by average SEITC to provide evidence that families who receive SEITC are not fundamentally different from families in the same income bracket who do not.

Model Results

The ECLS-B provides weights to adjust for participants' representation in the population as well as participant response rateand so two sets of analyses are presented: one for analyses on the unweighted data, and another for analyses with weights for longitudinal analyses in the ECLS-B. Results are presented in the following order: 1) school readiness skills, 2) cognitive stimulation, 3) childcare quality, 4) changes in estimates with depression added as a control, and 5) mediation. Because the interaction between average benefit and number of dependent children was necessary to produce a strong enough predictor of benefits, results should be interpreted as generalizable for families with 2.48 or more children. See Table 19 for estimates of the main effect of benefits and Table 20 for estimates of the interaction between benefits and race/ethnicity.

Long Format Analyses, Unweighted

School readiness skills.

There was no effect of benefits on Bayley Mental Development Index scores ($p > .05$). It is important to note that Bayley Mental Development Index was assessed at the first two waves, and the effect of benefits is lagged (i.e., benefits_{t-1} predicts Bayley scores at t), and so the random effect of time nested within families was not included. Moreover, unlike the other models presented, the model predicting Bayley Mental Development Index leverages data from a single assessment, making its ability to detect effects under-powered relative to the other models presented.

See Figures 12 and 13 for the relation between SEITC and school readiness skills, while taking into account income range. Results indicated that there a $1,000 increase in benefits predicted .06 SD increase in math skills (t = 1.91). While the ECLS-B did not get exact income for every family, the effect of benefits on math skills was similar in magnitude to going from the bottom income range (0 - $5,000) to the second ($5,000 - $10,000) or fifth ($20,001 to $25,000; the school readiness skills of children in the third and fourth income range did not reliably differ from children in the first). In addition, the effect of benefits was also allowed to interact with child race/ethnicity. Results indicated that the effect of benefits did not differ by race/ethnicity. When interacting benefits with race/ethnicity, the effect of benefits on math skills was not statistically reliable for any race/ethnicity (White, Black, Hispanic, Asian, Native Hawaiian, Native American, and more than one race/ethnicity; $t < 1.96$).

Results also indicated that a $1,000 increase in benefits predicted a .10 SD unit increase in reading skills (t = 2.77). While the ECLS-B did not get exact income for every family, the effect of benefits on math skills was similar in magnitude to going from the bottom income range (0 - $5,000) to the second ($5,000 - $10,000) or fifth ($20,001 to $25,000; the school readiness skills of children in the third and fourth income range did not reliably differ from children in the first). In another model, the effect of benefits was allowed to interact with child race/ethnicity. Results indicated that benefits did not predict an increase in reading skills for Black families. For Black, a $1,000 increase in benefits predicted a reduction in reading skills by .30 SD units, relative to White families for whom a $1,000 increase in benefits predicted a .22 SD unit increase in reading skills (t = 3.53). The effect of benefits was reliably different from the effect of benefits for White families for any other race/ethnicity (Hispanic, Native Hawaiian, Native American, and more than one race/ethnicity; $p > .05$).

Cognitive stimulation.

There was no effect of benefits on maternal reported book reading ($t < 1.96$).

Childcare.

There was no effect of benefits on type of childcare ($t < 1.96$).

Childcare Quality.

There was no effect of benefits on childcare quality ($t < 1.96$).

Depression as a control.

Including maternal depression as a control variable left the results largely unchanged. Results indicated that the effect of benefits on math skills increased slightly to .07 (p = .005), and the effect of benefits on reading skills remained .12 (p = .013).

Mediation.

Mediation was not tested because there was no effect of benefits on the proposed mediators.

Summary: Unweighted.

Results indicated a consistent positive effect of income on children's reading and math skills. Surprisingly, an increase in benefits did not appear to improve the school readiness skills of Black children. The effect of income was not altered by the inclusion of maternal depression as a control variable, and the effect was not mediated by cognitive stimulation or childcare.

Long Format Analyses, Weighted

School readiness skills.

Results indicated that there was no effect of benefits on the Bayley Mental Development Index (p > .05). Results indicated that a $1,000 increase in benefits predicted a .07 SD unit increase in math skills (t = 2.09). While the ECLS-B did not get exact income for every family, the effect of benefits on math skills was similar in magnitude to going from the bottom income range (0 - $5,000) to the third ($10,000 - $15,000) or fifth ($20,001 to $25,000; the school readiness skills of children in the second and fourth income range did not reliably differ from children in the first). Allowing benefits to interact with child race/ethnicity again indicated there was no effect of benefits for Black families. For Black families, a $1,000 increase in income predicted a .30 SD unit decreasing in reading skills, relative to the .16 SD unit increase observed in White families (t = -3.30). There was not a statistically reliable difference in the effect of benefits for any other racial/ethnic group.

Results also indicated that a $1,000 increase in benefits predicted a .13 SD unit increase in reading skills (t = 3.20). While the ECLS-B did not get exact income for every family, the effect of benefits on math skills was similar in magnitude to going from the bottom income range (0 - $5,000) fifth ($20,001 to $25,000; the school readiness skills of children in the second through fourth income range did not reliably differ from children in the first). Allowing benefits to interact with child race/ethnicity indicated that benefits were not beneficial for Black families and were less beneficial for Hispanic families. For Black families a $1,000 increase in income predicted a .40 SD unit decrease in reading skills, relative to the .30 SD unit increase observed for White families (t = -4.30). For Hispanic families, a $1,000 increase in benefits predicted a .18 SD unit decrease in reading skills relative to the .30 SD unit increase observed for White families (t = -1.94). The effect of benefits was not reliabily different form the effect observed for White families for any other race/ethnicity.

Cognitive stimulation.

There was no effect of benefits maternal-reported book-reading or cognitive stimulation (t < 1.96).

Childcare.

There was no effect of benefits on type of childcare (t < 1.96).

Childcare Quality.

There was no effect of benefits on childcare quality (t < 1.96).

Depression as a control.

Including maternal depression as a control variable left the result largely unchanged. Results indicated that the effect of benefits on reading skills remained .13 *(t = 3.17).* In addition, the estimate on math skills was largely unchanged as well. Results indicated that the effect of benefits on math skills remained .07 *(t = 2.12).*

Mediation.

Mediation was not tested because there was no effect of benefits on the proposed mediators.

Summary: weighted.

Results indicated a positive effect of income on children's reading and math skills, but not on the Bayley Mental Development Index. Surprisingly, an increase in benefits did not appear to improve the school readiness skills of Black children. The effect of income was not altered by the inclusion of maternal depression as a control variable, and the effect was not mediated by cognitive stimulation or childcare.

Summary Study 2a

Results reliably indicated that income had a positive impact on both math and reading skills across both weighted and unweighted analyses. When maternal depression was added as a control variable, the estimates of interaction between income and dependent children on reading and math skills remained unchanged. Moreover, the effect of benefits was not mediated by childcare or cognitive stimulation.

Study 2b: Instrumental Variables – Minimum Wage Increases

Study 2b examines the impact of income on school readiness skills for families whose mothers earn the minimum wage. An ordinary least squares regression between income and school readiness skills provides a biased estimate of the effect of income. Minimum wage workers who earn more also work more, and working more is associated with a host of other possible confounds that hours worked can only go so far to control. For example, a parent who works more may be employed at a stressful job or have less time to spend with their children. Moreover, families in states with the least generous minimum wage may work the most hours just to make ends meet. An ordinary least squares regression places these families in the treatment group, when they may face more disadvantages than families earning slightly less but receiving better pay and working fewer hours.

For the second instrument, the present dissertation uses state and federal minimum wage increases as an instrument for income. This approach places families whose increased income came from an increase in the minimum wage, and compares the school readiness skills of their children to families whose income did not increase because their state did not raise the minimum wage. From 2000-2010, 34 states increased their minimum wage, from increases as low as 2 cents per hour, to as large as $1.50 per hour. Please see Figure 14 for density plots of the minimum wage at each time point. While it is impossible to say exactly how much a person would have made if the minimum wage was not increased, it is possible to give an approximation.

Variation in benefits represents an instrument that satisfies the four assumptions of an instrumental variables estimation strategy. *Ignorability of the instrument*. In order for this assumption to be violated, participants would have to interact with the minimum wage increases. It is possible that workers in states that raised the minimum wage were different than those in states that did not, but this difference can be statistically controlled with the inclusion of state as a control variable. It is possible that a minimum wage increase forced out more disadvantaged workers – research suggests that minimum wage increases draw more economically advantaged teenagers into the minimum wage labor market, and their entrance subsequently pushes out economically disadvantaged young adults and teenagers (Giuliano, 2013). Thus, while the minimum wage increase may be unexpected for the minimum wage workers, it is possible that only the more advantaged of minimum wage workers were able to benefit from the increase. This possibility would bias the results upward because the control group would contain all minimum wage workers, while the treatment group may contain only the more advantaged minimum wage workers. The present dissertation examines differences in control variables as a function of minimum wage increases to examine whether there are differences in observable variables as a function of minimum wage increases. Null associations, particularly in education, would suggest that employers were not hiring more affluent teenagers at the expense of low-income adults because employers are more likely to retain more educated employees, and more education generally reflects more advantage. *Nonzero association between instrument and treatment variable*. For a minimum wage worker working 40 hours a week, a $1 increase in the minimum wage represents a $2,080 increase in wages, suggesting there is a strong relation between minimum wage increases in wages. The present dissertation tests this assumption via recommendations by Staiger and Stock (1994). *Monotonicity*. It is impossible for people to refuse the increase in the minimum wage, as it is mandated by law. The monotonicity assumption is thus satisfied by definition of how minimum wage increases operate. *Exclusion restriction.* For this assumption to be violated, school readiness skills would have to be affected by variation in an increase in the minimum wage through avenues other than increased family income. It is unlikely that variation in increases in the minimum wage for families would affect school readiness skills through avenues other than increased income because the minimum wage increases directly affect participants' income.

A mathematical representation of minimum wage increase as an instrument for income is as follows:

$$\text{Income}_{tiks} = \beta_0 + \beta_1 X_{tiks} + \beta_2 \text{MinimumWage}_{tks} + \varepsilon_{tiks} \quad (1)$$

where the indices on the variables represent state (s), time (t), number of children (k), and families (i). The vector X contains controls that include time, state, number of children, maternal education, employment and marital status. The present dissertation also controls for the second order interaction between state and time. The present dissertation does not control for second-order interactions with dependent children because the minimum wage, unlike benefits, is not based on number of children. The equation used to predict outcomes is as follows:

$$\text{Outcome}_{tiks} = \alpha_0 + \alpha_1 X_{tiks} + \alpha_2 \text{Income}_{tiks} + \eta_{tiks} \quad (2)$$

Where the indexes on the variables represent states (s), time (t), number of children (k), and families (i). Again, the vector X contains controls that include year, state, number of children, maternal education, and marital and employment status. Income is the predicted value of income based on Equation 1. The estimates provided by Equation 2 can be interpreted as the impact of an additional $1,000 in income, for families whose additional income came from variation in the minimum wage.

Participants

The participants in this study are a subset of the larger ECLS-B. To focus on families who made the minimum wage, the present dissertation focuses on families who reported their exact income and calculates participants' hourly wage by dividing their reported income by the number of hours a week they said they worked. The present dissertation further divides this number by 52 to arrive at an estimate of their hourly wages. The present dissertation then calculates the standard error of the hourly wage, and created an upper bound (hourly wage + standard error) and lower bound (hourly wage – standard error). The present dissertation retains participants who lived in states where the minimum wage was within the identified bounds.

548 families earned the minimum wage at some point during the course of the ECLS-B. 23% of these participants were White, 38% were Black, 22% were Hispanic, 3% were Asian, 7% were Native American, and 9% identified with more than one race/ethnicity. The mean income was $14,480. See Tables 21, 22, and 23 for participant descriptive statistics at each wave. No participants that earned the minimum wage were in the childcare sample.

Study 2b: Results

Please see Tables 24 through 28 for descriptive statistics and correlations at each wave. Minimum wage increases ranged from -$-.96 to $3.14/hour (adjusting to 2016 dollars). See Figures for density plots of the mean minimum wage at each wave. Of note, collinearity is an issue between income and hours. Hours worked was controlled for because parents' decisions about their hours worked, and thus their annual income, is likely influenced by the minimum wage – some parents might work more hours to take advantage of the increased wage, whereas other might work less to maintain the same standard of living. Parents' tendency to work more, less, or the same in response to minimum wage increases is likely influenced by unobservable variables. Controlling for hours to get predicted values of income helps to control for these unobservable variables. The predicted values of income can be thought of as isolating the effect of increase in income on the minimum wage irrespective of hours worked.

Data analysis of Study 2b is presented in the following order: 1) sample examination, 2) nesting structure examination, 3) the strength of the instrument examination, and 4) model results. All analyses were performed with lme4 (Bates, Maechler, Bolker, & Walker, 2014).

Sample Examination

Before model building, the relation between minimum wage increases and available participant characteristics that were used as control variables was examined. Results indicated that minimum wage increases did not share a relation with education, number of children, marital status, subsidy use, hours worked, or race/ethnicity, which suggests that participants employed in jobs in states and years where the minimum wage was raised were comparable to those in states and year where the minimum wage was not raised ($p > .05$).

Nesting Structure

Model building consisted of the same steps as in Study 2a: 1) the optimal nesting structure was first examined, and then the strength of the instruments – how well minimum wage raises predicted income – was examined.

In the ECLS-B there are two potential levels of nesting: time nested within families, and families within states. To decide on the optimal nesting structure, the need for inclusion of random intercepts was first explored by examining the amount of clustering that exists at the family level within the dataset via the ICC and the AIC. The random effect of state was not included because state was modeled as a fixed effect.

According to the ICC, 32.78% of the variance in benefits was attributable to similarity in income within families. An additional 22.14% of the variance was attributable to similarity in income within states. There was not enough data to allow the effect of time to vary within families: there were only 640 total observations, and allowing time to vary within families would have required at least 1,064 observations. The final nesting structure, with time nested within families, can be depicted as follows:

$$Income_{ti} = \beta 0_{ti} + r_{ti}$$

$$\beta 0_{ti} = \gamma_{0i} + \mu_i$$

where i = individuals and t = time. The control variables included in the equation were nearly identical to those in Study 2a: 1) time, 2) subsidy use, 3) child race, 4) child sex, 5) child age, 6) marital status, 7) hours worked, 8) dependent children, 9) education, and 10) state. Unlike in Study 2a, the second-order interactions between time and dependent children, and state and dependent children were not controlled for because unlike benefits, the minimum wage does not vary by dependent children. Models were also run without random effects because only a small number of participants earned the minimum wage at more than one occasion (N = 81), and results remained consistent with and without random effects.

With control variables included, the full model used is as follows:

$$Income_{tis} = \beta 0_{tis} + \beta 1\mathrm{X}_{tis} + MinimumWage_{tis} + r_{tis} \text{ (Step 1)}$$

$$\beta 0_{tis} = \gamma_{0i} + \mu_i$$

$$School\ Readiness_{tis} = \beta 0_{tis} + \beta 1\mathrm{X}_{tis} + \beta 2INCOME_{tis} + r_{tis} \text{ (Step 2)}$$

$$\beta 0_{tis} = \gamma_{0i} + \mu_i$$

Strength of Instrument

With the control variables included, the strength of the instrument was examined by comparing model fit via a Wald test, adjusting for clustered standard errors at the family and state levels. As a general rule of thumb, an F value greater than 10 (Staiger & Stock, 1994) provides evidence that the instrument is a sufficiently strong predictor of the endogenous predictor (i.e., benefits). Like in Study 2a, the present dissertation performs separate analyses for the Bayley Mental Development Index, school readiness skills, maternal reported book reading, and childcare type and quality. As such, the present dissertation tests the strength of the minimum wage as an instrument before Wave 3 (for the Bayley Mental Development Index), before Wave 4 (for childcare type and quality), after Wave 2 (for school readiness skills), and over the whole sample (for maternal reported book reading). The predicted values for each outcome are also obtained from each separate first stage equation.

Results indicated that over the whole sample, the mean minimum wage was a strong predictor of income ($F(1, 501) = 51.96$, $p < .001$). Before Wave 3, the mean minimum wage was not a strong predictor of income ($F(1, 209) = 5.48$, $p = .020$). Because the mean minimum wage was not a strong instrument for income prior to Wave 3, the present dissertation does not test for the effect of income on the Bayley Mental Development Index. Before Wave 4, the mean minimum wage was a strong predictor of income ($F(1, 379) = 14.68$, $p < .001$). Finally, after Wave 2, the mean minimum wage was a strong predictor of income ($F(1, 202) = 19.86$, $p < .001$). All models were performed in lme4 (Bates et al., 2014).

Model Results

Results are presented first for unweighted analyses, and then again for weighted analyses. See Table 29 for the main effect estimates of income, and Table 31 for interactions with race/ethnicity. See Figures 15 and 16 for a depiction of the effect of the second stage of income on school readiness skills.

Unweighted

School readiness skills.

In contrast, results indicated that a $1,000 increase in income predicted a .05 SD unit increase in math skills ($p = .055$). This estimate was much larger than the estimate from an ordinary least-squares regression: in an ordinary least squares regression, the effect of a $1,000 increase in income on math skills was .01. Allowing benefits to interact with child race/ethnicity indicated that there was an additional effect of income for families who identified as more than one race. For families who identified as more than once race, a $1,000 increase in benefits predicted an additional .10 SD unit increase in benefits, on top of the .04 SD unit increase in benefits for White families ($p < .001$).

Results also indicated that a $1,000 increase in income predicted a .09 SD unit increase in reading skills ($p = .003$). This estimate was much larger than the estimate from an ordinary least-squares regression: in an ordinary least squares regression, the effect of a $1,000 increase in income on reading skills was .03. Allowing benefits to interact with child race/ethnicity indicated that the effect of wages was even greater for Asian families; for Asian families, a $1,000 increase in income predicted an additional .11 SD unit increase in reading skills ($p = .032$), on top of the .08 SD unit increase for White families.

Cognitive stimulation.

There was no effect of benefits on maternal reported book reading ($p > .05$).

Childcare.

Results indicated that a $1,000 increase in income predicted an increase in the probability of the use of parental care by 16.47% ($p < .001$), an increase in the probability of use of other care by 3.00% ($p = .012$), and a decrease in the probability of Head Start by 3.23% ($p < .001$). There was no effect of income on the probability of use of center-based childcare (non-relative or relative).

Depression as a control.

Adding maternal depression as a control increased the size the effect of income on school readiness skills: with depression as a control, the effect of income on math skills increased to .06 ($p = .029$), and the effect of income on reading skills increased to .10 ($p = .003$).

Mediation.

Mediation by maternal-reported book reading was not assessed because income did not have an effect on maternal-reported book reading (p > .05). A concurrent mediation analysis was performed. A prospective mediation analysis was not examined because, out of the 548 families who earned the minimum wage, only 84 of those families earned the minimum wage at more than one time. As such, as prospective mediation analysis could only produce results for at least 84 families, but in practice even less than that, given that childcare was and school readiness skills were only assessed at certain waves.

Results indicated childcare did not mediate the relation between income and school readiness skills. The effect of income on math and reading skills focusing just on Wave 3 was larger than the combined waves (β = .13, p = .001, and β = .15, p < .001). With the inclusion of parental childcare, other childcare, and Head Start dummy variables (only these dummies were included because there was only an effect of income on those two types of childcare) the estimate on math skills slightly increased to .14 (p < .001), and the estimate on reading skills increased to .19 (p < .001).

Summary.

Results indicated that an increase in income had a positive association with math and reading skills, but not the Bayley Mental Development Index. In addition, the inclusion of maternal depression as a control variable did not alter the estimate of income on math or reading skills, and the effect of income was not mediated by cognitive stimulation or childcare.

Weighted

School readiness skills.

In contrast, results indicated that a $1,000 increase in income predicted a .05 SD unit increase in math skills (p = .081). This was result was drastically larger than the estimate from an ordinary least squares regression, in which a $1,000 increase had an effect close to zero (β = .001). Allowing income to interact with child race/ethnicity indicated additional benefits for Hispanic families as well as families who identified as more than once race. For Hispanic families, a \$1,000 increase in benefits predicted an additional .04 SD unit increase in reading skills, on top of the .03 SD unit increase estimated for White families (p = .06). For families who identified with more than one race/ethnicity, a \$1,000 increase in income predicted an additional .13 SD unit increase in reading skills, on top of the .03 SD unit increase estimated for White families (p < .001).

Results also indicated that a \$1,000 increase in income predicted a .10 SD unit increase in reading skills (p =.004). Results from an ordinary least-squares regression suggested that such an analysis underestimates the impact of income on math skills: with an ordinary least-square regression, a \$1,000 increase in income had a smaller effect (β = .04). Allowing income to interact with child race/ethnicity indicated additional benefits for Hispanic families as well as families who identified as more than once race. For Hispanic families, a \$1,000 increase in benefits predicted an additional .07 SD unit increase in reading skills, on top of the .06 SD unit increase estimated for White families (p = .008). For families who identified with more than one race/ethnicity, a \$1,000 increase in income predicted an additional .08 SD unit increase in reading skills, on top of the .06 SD unit increase estimated for White families (p = .024).

Cognitive stimulation.

There was no effect of wages on maternal-reported book reading (p > .05).

Childcare.

Results indicated that a \$1,000 increase in income increased the probability of use of parental care by 4.01% (p = .012). An additional \$1,000 in income also decreased the probability of the use of Head Start by 2.69% (p < .001).

Depression as a control.

Adding maternal depression as a control increased the size of the effect of income on math and reading skills. For math skills, with depression entered as a control, the effect of income increased from .05 to .09 (p = .003), and for reading skills, the effect income increased from .10 to .16 (p < .001).

Mediation.

A concurrent mediation analysis was performed. A prospective mediation analysis was not examined because, of the families who earned the minimum wage, only 84 of those families earned the minimum wage at more than one time. As such, as prospective mediation analysis could only produce results for at least 84 families, but in practice even less than that, given that childcare was and school readiness skills were only assessed at certain assessments.

Results again indicated that childcare did not mediate the relation between income and school readiness. Focusing just at Wave 3, when both childcare and math and reading skills were measured, a $1,000 increase in income predicted a .07 SD unit increase in math skills (p = .006). With parental care and Head Start entered as predictors into the model, a $,1000 increase in income predicted a .22 SD unit increase in math skills (p < .001). Similarly, without childcare entered in the model, a $1,000 increase in income predicted a .03 SD unit increase in reading skills (p = .184), and with parental care and Head Start, a $1,000 increase in income predicted a .26 SD unit increase in math skills (p < .001).

Summary.

Results indicated that an increase in income had a positive association with math and reading skills, but not the Bayley Mental Development Index. In addition, the inclusion of maternal depression as a control variable did not alter the estimate of income on math reading skills, and the effect of income was not mediated by cognitive stimulation or childcare.

Summary: Study 2b

Results indicated a positive effect of income on reading and math skills in the weighted and unweighted analyses. The effect of income on math skills was not statistically precise in the weighted analysis; however, with the inclusion of maternal depression as a control variable, the effect of income on both reading and math skills was statistically precise. The effect of income was not mediated by cognitive stimulation or childcare.

Discussion

Summary

While results from the change score model suggest that income does not impact cognitive stimulation, results from the instrumental variables estimation of the present dissertation suggest that income has a substantial impact on children's reading and math school readiness skills (Note: while Study 2a measured the impact of benefits while controlling for family income range, the present dissertation refers to benefits as income as well, unless otherwise noted because benefits represent an additional boost an income that families receive at the end of the year). Results from instrumental variables are more reliable than results from the change score models because change score models can still be biased from time-varying covariates (Angrist & Pischke, 2008). Moreover, research suggests that a standard ordinary least squares regression underestimates the impact of income on school readiness skills, which casts further doubt on the accuracy of the results from the change score model (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). Neither cognitive stimulation nor childcare mediated the relation between income and school readiness skills. As such, the hypotheses of the proposed dissertation were partially supported. An increase in income predicted an increase in both math and reading skills in the ECLS-B, as hypothesized. However, contrary to expectations, this effect was not mediated by cognitive stimulation or childcare, and the effect of income on math and reading skills was not observed in the SECCYD.

There are several reasons why results differed by method and sample used. First, a change score model may be an incorrect approach to modeling the relation between income and school readiness skills. Income varies in families for a variety of reasons, many of which vary over time: a promotion at work, extended time off due to an illness or death in the family, or being let go from work, to name just a few. A change score model lumps the effect of change in income along with the myriad of potential reasons why income changes, thereby obscuring the effect of income. In addition, the SECCYD may have been an inappropriate sample to test the effect of change in income. The SECCYD is a relatively affluent sample, but past research has identified the effect of income with low-income samples. Although the present dissertation did examine whether the effect of income varied by income group within the SECCYD, a relatively small number of families were in the bottom income quartile (N = 280). Finally, the SECCYD, and in particular the preschool assessments, occurred during a period of relative prosperity in the United States. It is possible that an effect of change in income was not observed because a majority of families were experiencing an increase in income, making an appropriate control group difficult to estimate, particularly because change score models estimate he effect of income within families.

Policy Relevance

The size of the effect differed by the technique used; variation in income from increases in benefits produced somewhat larger estimates than variation in income from the SEITC. However, at even the lower bound, results of the present dissertation are policy relevant, for *both* reading and math skills. At the lower bound, results indicated that a $1,000 increase in income predicted a .05 SD unit increase in math skills. While the effect per $1,000 may be small, it is important to keep in mind that families often receive thousands of dollars in benefits (the maximum EITC for a family of three is approximately $6,000), and a $2 wage increase for someone that works forty hours a week results in an additional $4,160 a year. If a family sees a $4,000 increase in income, children in that family could expect to see a .20 SD unit increase in their math skills. Results suggested an even stronger effect of income on reading skills. At the lower bound, results indicated that a $1,000 increase in income predicted a .09 SD unit increase in reading skills. Again, per $1,000 the effect may be small, but a family receiving an additional $4,000 from benefits or wage raises could expect to see a .36 SD increase in their reading scores. At the higher bounds, results are even more striking. Results indicated that a $1,000 increase in income predicted a .07 SD unit increase in math skills and a .13 SD unit increase in reading skills; children in families receiving an additional $4,000 could expect to eliminate approximately a quarter to a half of the gap in school readiness skills between themselves and their more economically advantaged peers. The effect sizes are even more noteworthy when considering how much students learn within a year. Research suggests that students gain approximately 1.2 to 1.5 standard deviations in math and reading between fourth and eighth grade (Reardon, 2011). Assuming that gains follow a similar trajectory in preschool, one school year is equal to approximately .30 and .375 SD units. Results of the present dissertation suggest that increasing income by $4,000 could boost children's school readiness skills by an amount equivalent to at least a school year, and at most more than a year.

The effect of income is not only large, but also cost-effective. As noted in Duncan et al. (2012), the Tennessee Star Experiment, which reduced class size in elementary school classrooms, produced a .25 SD unit increase in child achievement in third grade, at the cost of $7,500 per child. It is not sound to extrapolate the results of the present dissertation beyond increases in income observed in the present study; however, $4,000 in increased income was observed in the present study, and so results suggest that increasing income may be at least as effective, for less money, than the Tennessee Star Experiment.

Context with Other Research

Results of the present dissertation add to a body of evidence that suggests that income aids children's cognitive development. A $1,000 increase in income corresponds to a 5-7% SD increase in child achievement (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011). In the present dissertation, the effect of income on math skills was similar in magnitude to the effect of income on child achievement (β = .05 - .07 and β = .05 - .07, respectively), while the effect of income on reading skills was larger than the effect of income on child achievement (β =.09 - .13 and β = .05 - .07, respectively). The discrepancy between effect sizes may be because children are particularly susceptible to the environment earlier in development (Ramey & Ramey, 1998), and children are saturated with opportunities to boost reading skills in early childhood – parents can read books, teach the alphabet, and children can watch educational television shows (Bassok, Finch, Lee, Reardon, & Waldfogel, 2016; Rice, Huston, Truglio, & Wright, 1990), to name a few of the avenues that promote reading skills. In short, children can take advantage of numerous opportunities to boost their children skills *at a critical time*. In contrast, the effect of income on math skills may be smaller because preschool-aged children are not saturated with opportunities to learn math before formal schooling, and so there is limited opportunity to boost math skills (Bassok et al., 2016).

Results of the present dissertation were consistent with research that suggests that an ordinary least squares regression of income onto children's cognitive development underestimates the impact of income (Dahl & Lochner, 2012; Milligan & Stable, 2011). For decades, researchers have noted the correlation between income and child achievement, and more recently, the correlation between income and school readiness skills (Lee & Burkam, 2002; Mayer, 1997). The present study, along with other studies examining the link between income and child achievement, suggest that the link between income and children's cognitive development is not spurious (Dahl & Lochner, 2012; Duncan et al., 2011; Milligan & Stable, 2011), as some have suggested (Mayer, 1997). Instead, a converging body of evidence suggests that the decades-long body of correlational evidence may have *underestimated* the impact of income on children's cognitive development. In a correlational analysis, families that earn the most receive the largest doses of treatment, but research suggests that income has a stronger relationship with child achievement for families with less money (Dearing, McCartney, & Taylor, 2001). So, in a correlational analysis, children for whom income no longer has a strong impact are considered part of the treatment group, which underestimates the impact of income.

Results of the present dissertation suggested that the effect of income was generally consistent across families. However, the present dissertation also found negative effects of benefits on reading and math skills for Black families. Black families often live in the most disadvantaged neighborhoods in the United States (Sharkey, 2014). It is possible that the effect of income, while beneficial, was mitigated by increased crime and diminished resources often seen in disadvantaged neighborhoods, so that Black families did not see the additional benefit that other families saw. Moreover, the SEITC is meant to encourage employment. Research on the EITC has found that it did indeed encourage families to work, but many families placed their children in low-quality childcare in response to increased employment, which resulted in a reduction in school readiness skills (Herbst & Tekin, 2010). Future research should examine this effect further, and to identify why increased benefits may have a negative impact for Black families.

The present study is at odds with past research that suggested that cognitive stimulation may mediate the impact of income on school readiness skills. According to a large body of research stemming from the Family Investment Model (Haveman & Wolfe, 1984), cognitive stimulation may explain the relation between income and children's cognitive development because families with more income are able to invest more in promoting their children's cognitive development (Linver et al., 2002; Yeung, Linver, & Brooks-Gunn, 2000). The present dissertation found no evidence that cognitive stimulation acted as a mediator.

The present dissertation did find some support that childcare mediates the link between income and school readiness skills. Research suggests that high-quality childcare is particularly beneficial for economically disadvantaged children (Duncan & Magnusson, 2013), and economically advantaged children often attend higher quality childcare than their economically disadvantaged peers (Howes et al., 2008). The present dissertation found that increases in income that came from increases to the minimum wage were associated with a lower probability of attending Head Start and a higher probability of parental care, which is often of lower-quality than Head Start. Moreover, results suggested that including Head Start and parental care as control variables increased the size of the effect of income on school readiness skills. A lower probability of attending Head Start and increased probability of parental care, along with an increased effect size of income while controlling for parental care and Head Start provides evidence that childcare is not a mediator in low-income samples. But it does provide some evidence that childcare may be mediator of the link between income and school readiness skills across the distribution of income. As low-income workers earn more, they may lose access to high-quality childcare, potentially widening the gap in school readiness skills between low income and high income children. Results of the present dissertation suggest that controlling for childcare type (i.e., assuming that all children attend the same childcare type) the effect of income is school readiness skills is much stronger. With more money and consistent access to high-quality childcare, children from low-income families may be able to make up more of the gap in school readiness skills between themselves and their more economically advantaged peers.

It is also possible that cognitive stimulation and childcare quality are correlates, but not causes of increased school readiness skills. Cognitive stimulation may be on average diminished among economically disadvantaged families, and economically disadvantaged children may attend lower quality childcare, but diminished cognitive stimulation and low-quality childcare may not be the cause of lower school readiness skills. Rather, there may be substantial heterogeneity in the *cause* of lower school readiness skills: for one family, it is certainly possible that their child displays lower school readiness skills because of limited cognitive stimulation (Conger & Donnellan, 2007), but for another, it is possible that their child displays lower school readiness skills because of poor childcare quality (Duncan & Magnuson, 2015). For yet another, it is possible that their child displays lower school readiness skills because of a health problem that interferes with learning (Fowler, Johnson, & Atkinson, 1985). With increased income, families may able to decide which of these barriers to divert their extra income to in order to support the cognitive development of their children.

It is also possible that neither cognitive stimulation, childcare quality, nor health explain the lower school readiness skills of economically disadvantaged children in isolation, but rather their *culmination* (Sameroff, Bartko, Baldwin, Baldwin, & Seifer, 1998). Risk factor research consistently finds that it is not any one risk factor that explains disparities in health, mental health, or education, but rather the culmination of risk factors (Sameroff et. al, 1998). With increased income, families may be able to address each barrier to their children's cognitive development simultaneously.

Strengths

The present dissertation is the first study to provide sound causal evidence on the link between income and school readiness skills. Researchers have found consistent links between family income and child achievement (Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011; Milligan & Stable, 2011), but no research has examined the link between income and school readiness skills. The present dissertation adds an additional developmental period on which income has a substantial impact. A growing body of literature now suggests that increasing income would boost economically disadvantaged children's school readiness skills across development – in preschool, elementary school, *and* high school (Dahl & Lochner, 2012; Duncan, Morris, & Rodrigues, 2011; Milligan & Stable, 2011). The present dissertation is also the first to examine increases in the minimum wage as an instrument for income. Minimum-wage workers are a particularly vulnerable population, and the present study is the first to show that raising the minimum wage can benefit the cognitive development of their children. Results of the present dissertation were robust. Although effect sizes varied somewhat, results consistently showed a positive association between income and school readiness skills at Waves 3, 4, and 5 – when children were four to seven years olds. In contrast, the present dissertation did not find an impact of income on school readiness skills at Waves 1 and 2, when children were between 6 months and three years old.

Limitations

Though the study has many strengths, it cannot offer insight into how additional income would affect extremely poor and not-working families. Obviously, families have to be working to be affected by the minimum wage and EITC increases, and families earning less than $3,000 are prohibited from receiving the additional child tax credit. There is simply not enough information on the relation between income and child cognitive development for extremely poor and not-working families. The best information that exists comes from a study of welfare-to-work programs, which found that random assignment to those programs, and subsequent increased income, did boost children's achievement (Duncan et al., 2011). The families in these programs were extremely poor, but the causal effect estimate was for families who signed up for the programs – a motivated group of families. It is certainly possible that results would generalize to families who did not sign up for the programs, but future research is needed.

In addition, it is possible that the estimates in the minimum wage sample were upwardly biased because minimum wage workers who benefit from the wage increase may be more advantaged minimum wage workers. Research suggests that minimum wage increases draw more economically advantaged teenagers into the minimum wage labor market, and their entrance subsequently pushes out economically disadvantaged adults and teenagers (Giuliano, 2013). It is possible that only the more advantaged minimum wage workers benefitted from the increase in the minimum wage, which would bias the result upward. The present dissertation examined whether increases in the minimum wage predicted any participant characteristics and performed a separate set of analyses with workers who earned the minimum wage at more than one time point, but it is still possible that the minimum wage workers who experienced an increase were relatively advantaged. However, while the results may be biased upward, it is unlikely that the bias is so strong as to reduce the effect to zero.

The present dissertation did not find evidence that cognitive stimulation mediated the link between income and school readiness skills, but it is possible that other parenting practices, such as supportive parenting mediate the relation between income and school readiness skills. The link between supportive parenting and income was not tested because the developmental literature suggests that cognitive stimulation is more closely related to cognitive development than supportive parenting, while supportive parenting is more closely related to social-emotional development (Guo & Harris, 2000). Moreover, research that has examined the link between income and supportive parenting in a causal inference framework also has not found a relation between the two (Duncan et al., 2011; Duncan, Gennetian, & Morris, 2007; Morris, Huston, Duncan, Crosby, & Bos, 2001). However, these studies investigated the relation between income and child achievement in elementary school. It would be worthwhile to examine the relation between income and supportive parenting in future investigations because it is possible that supportive parenting mediates the link between income and cognitive development in preschool.

Also, the ECLS-B did not ask for income information for some participants, and so the present dissertation took a mean of possible benefits for families who gave a range of income, which introduced error into the measurement of benefits. It is unlikely, however, that the error was large enough to produce such consistent positive associations – taking a mean of possible SEITC payments would be off by hundreds of dollars, but the effect of SEITC was observed for thousands of dollars.

Finally, measurements issues may explain some of the null association. For example, poor measurement may have been the reason why mediation was not observed. Cognitive stimulation was measured via maternal-reported book reading in the ECLS-B, which is an extremely specific measure that misses other important parts of cognitive stimulation, like material goods in the home that promote cognitive stimulation and activities such as trips to the library. Moreover, the measures of childcare quality used in the ECLS-B, the ITERS and FDCRS, measures interactions with caregivers and peers, exposure to materials and activities, whether routine care needs are met, and the furnishings and displays in the classroom. These indicators do not tap into supportive interactions between teachers and children and intentional instruction, which are the qualities of childcare most associated with school readiness skills (Keys et al., 2014).

In addition, Poor measurement may also have been the reason for null findings in outcome measures. While internally reliable, the Bayley Mental Development Index shows poor predictive validity, at least in high-risk infants (Hack et al., 2005; Niccols & Latchman, 2002; Harris, Megens, Backman, & Hayes, 2005). It is possible that Bayley Mental Development Index does not accurately assess school readiness skills, and it also possible that prior to three years old is simply too early on to assess school readiness skills. Relatedly, the present study did not assess impacts of income on social-emotional skills or executive functioning. Given the importance of nurturing parenting early in life (Kalil, Ryan, & Corey, 2012), and the close link between nurturing parenting and social-emotional development (Thompson, 2008), it is possible that income may have reduced maternal stress, boosted nurturing parenting and subsequent social emotional development, as theorized by the Family Stress Model (Conger et al., 2002).

Future Research Directions

While the present study did not find a consistent mediator of the effect of income on children's school readiness skills, that does not mean that there is not a consistent mediator. Future studies should continue to explore what mediates the relation between income and children's cognitive development, and also examine if the reduction across an array of barriers mediates the link between income and children's cognitive development.

The present study added to the evidence on the effect of income on child cognitive development. Future studies should examine how an increase in income affects the *growth* of child cognitive development. For example, does an increase in income at critical periods in child development put children on a better path throughout childhood, or do those increases in income have to be sustained? Future research should examine how increases in income at different periods during child development affect children's trajectories.

The present study also did not address how an increase in income affects the chronically poor, who remain poor over a period of many years, versus the transitorily poor, who may experience poverty for a year or two. It is possible that the effects found in the present dissertation might differ by how families experience economic disadvantage, as research suggests that the families who experience chronic poverty may be more disadvantaged than those who are transitorily poor (Raver, Roy, & Pressler, 2015).

Finally, the present dissertation used causal inference techniques to examine the impact of income on school readiness skills. While instrumental variables estimation presents an effective strategy for identifying causality, a randomized control trial remains the gold standard of causal inference. An RCT, in which families in the treatment group were given an additional $1,000 per year, and control families were given a nominal fee, such as $200 per year, would greatly help to bolster evidence that income aids children's cognitive development.

Practitioner Implications

The findings of the present dissertation suggest that hopes for population—wide interventions, such as Providence Talks, that increase cognitive stimulation to boost the school readiness skills of economically disadvantaged children may be misplaced. This is not to say that interventions aimed at boosting the cognitive stimulation of children are for naught. To be clear, these interventions have value – there will always be families that would do well to engage in more cognitive stimulation. However, for these interventions to work on economically disadvantaged families as a population, one would expect for cognitive stimulation to at least partially mediate the relation between income and school readiness skills in the proposed dissertation.

That childcare did not appear to mediate the relation between income and school readiness skills is particularly promising for policy. Results of the present dissertation suggest that increases in income and access to high-quality childcare can act in tandem to boost the school readiness skills of economically disadvantaged children. Two-generation Head Start programs are a particularly promising intervention for boosting the school readiness skills of economically disadvantaged children. In two-generation Head Start Programs, services for both the child and parents are offered. Parents can receive job-training, adult education, and marriage and parenting support, among other services. Such an approach, in which children can receive high-quality childcare while parents learn skills that could boost their income may be even more effective than focusing on either avenue in isolation. However, it is important to reiterate an increase in income came from an increase to the minimum wage reduced the probability of attending Head Start in the present dissertation, presumably because families earned too much to qualify for Head Start. In order to support families as they transition to better-paying jobs, it is also crucial to maintain affordable services that benefit children.

Outside of interventions, the present dissertation adds to mounting evidence that suggests that increasing families' income is a worthwhile intervention strategy and that such an intervention is cost-effective. As detailed by Duncan (2012), the most effective preschool programs, the Carolina Abecederian Project and the Perry Preschool produced a 1.0 SD unit increase in IQ at age 3 for a cost of $40,000 per pupil and .60 SD unit increase in IQ, for $40,000 and $15,000, respectively. Moreover, the Tennessee Star Experiment, which reduced classroom size, also increased children's school achievement by .25 SD units for $7,500 per child. These effect sizes translate to a 2.5% SD unit increase in child academic achievement per $1,000 for the Carolina Abecederian Project, 4% SD unit increase in child achievement per $1,000 for the Perry Preschool Project, and a 3.3% SD unit increase per $1,000 for the Tennessee Star Experiment. Each of these effects is smaller than the observed effects of additional income both in the present study, as well as the larger body of literature that examines the link between income and child academic achievement.

Policy Implications

Results of the present study suggest that increasing family income either through more generous Earned Income Tax Credit or raises to the minimum wage would not only lift more families out of poverty but would also boost children's cognitive development. Moreover, there are many states that do not currently offer any percentage of the federal Earned Income Tax

Credit. Results of the present dissertation suggest that these states could provide a great benefit to families by offering some percentage of the federal Earned Income Tax Credit.

Moreover, results of the present dissertation suggest worthwhile points of intersection between advocacy groups and policymakers. For example, Fight for 15 is a national advocacy group that argues for a raise to the minimum wage. Results of the present study suggest that such a drastic increase in the minimum wage may have large effects on children's school readiness skills and child achievement. As such, activists interested in economic justice, and policymakers interested in educational attainment, may be able to forge a partnership in which both achieve their aims.

Conclusion

Educators, policymakers, and the general public agree that the disparity in educational attainment should be reduced, if not eliminated entirely. However, the gap between economically disadvantaged children and their more advantaged counterparts continue to grow. The present dissertation, along with a strong and accumulating body of evidence, suggests that increasing the incomes of these families is a worthwhile strategy to reduce the gap between economically disadvantaged children and their more economically advantaged peers.

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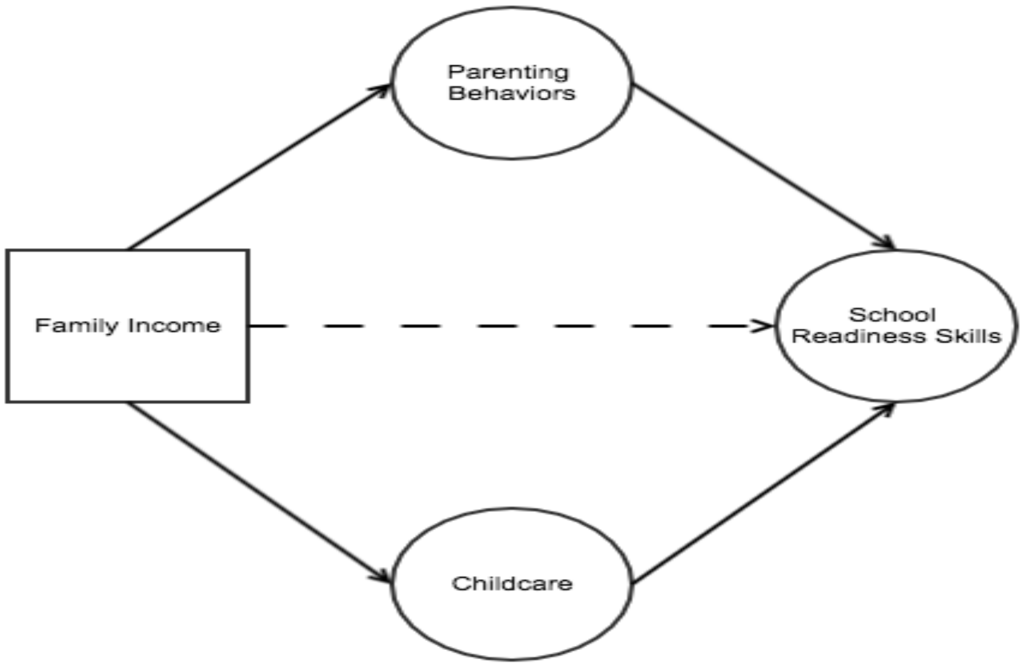
Figures



Figures

Figure 1. Proposed Mediation Model.

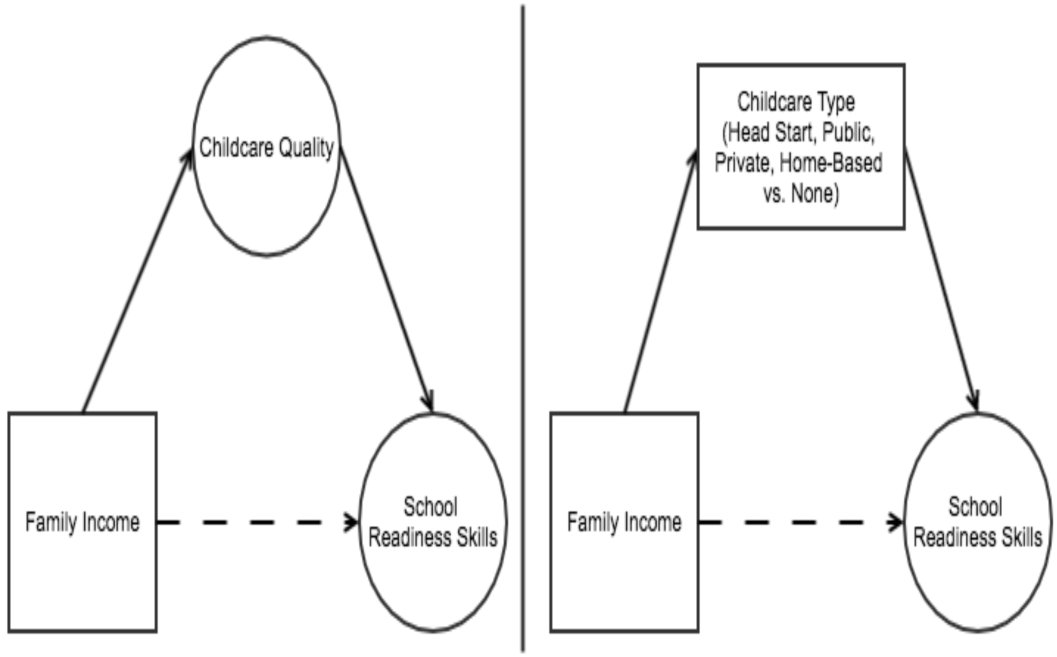


Figure 2. Two approaches to measure childcare quality.

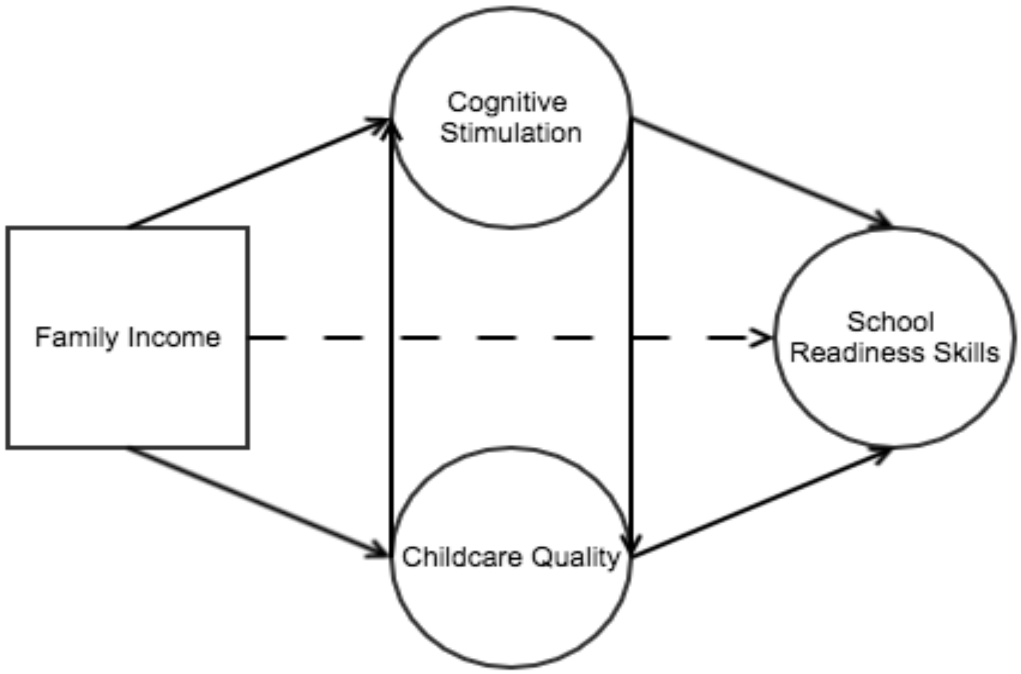


Figure 3. Reciprocal Relation Between Cognitive Stimulation and Childcare Quality.

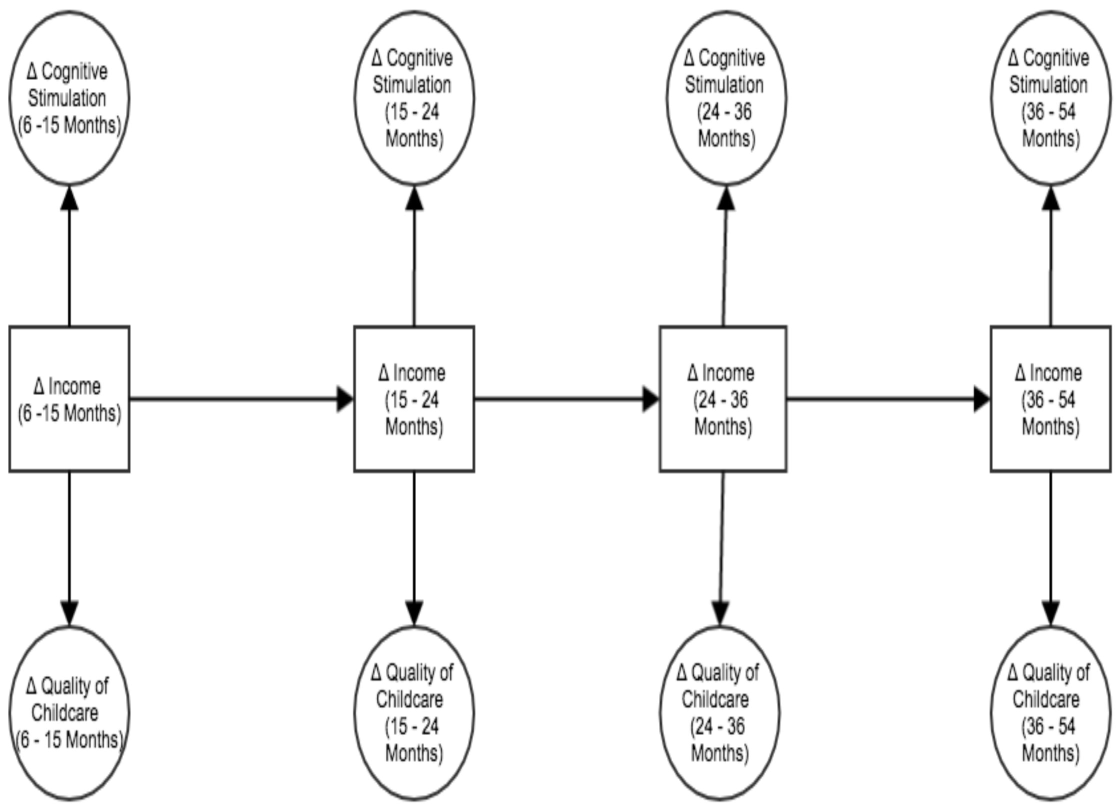


Figure 4. Proposed Model.

Note. School Readiness Skills is not drawn for ease of interpretation.

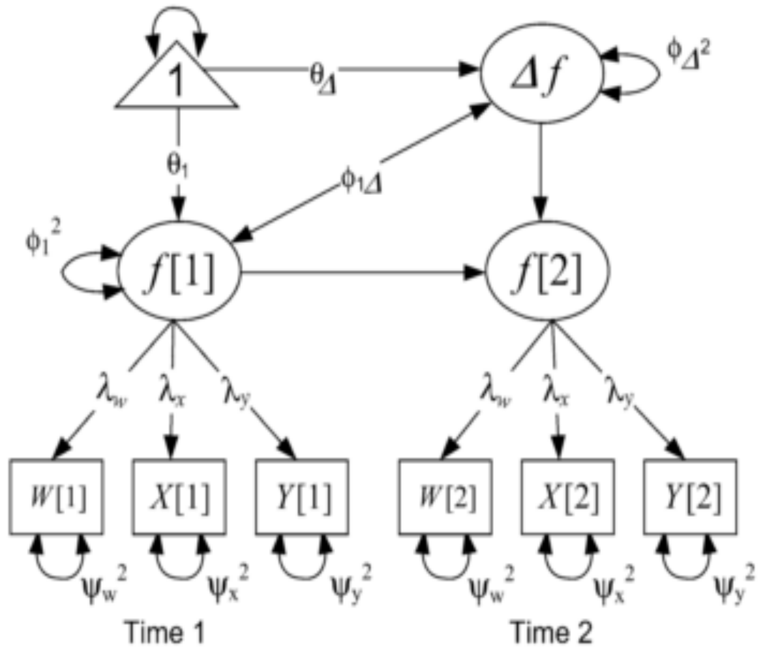


Figure 5. Latent Difference Score.

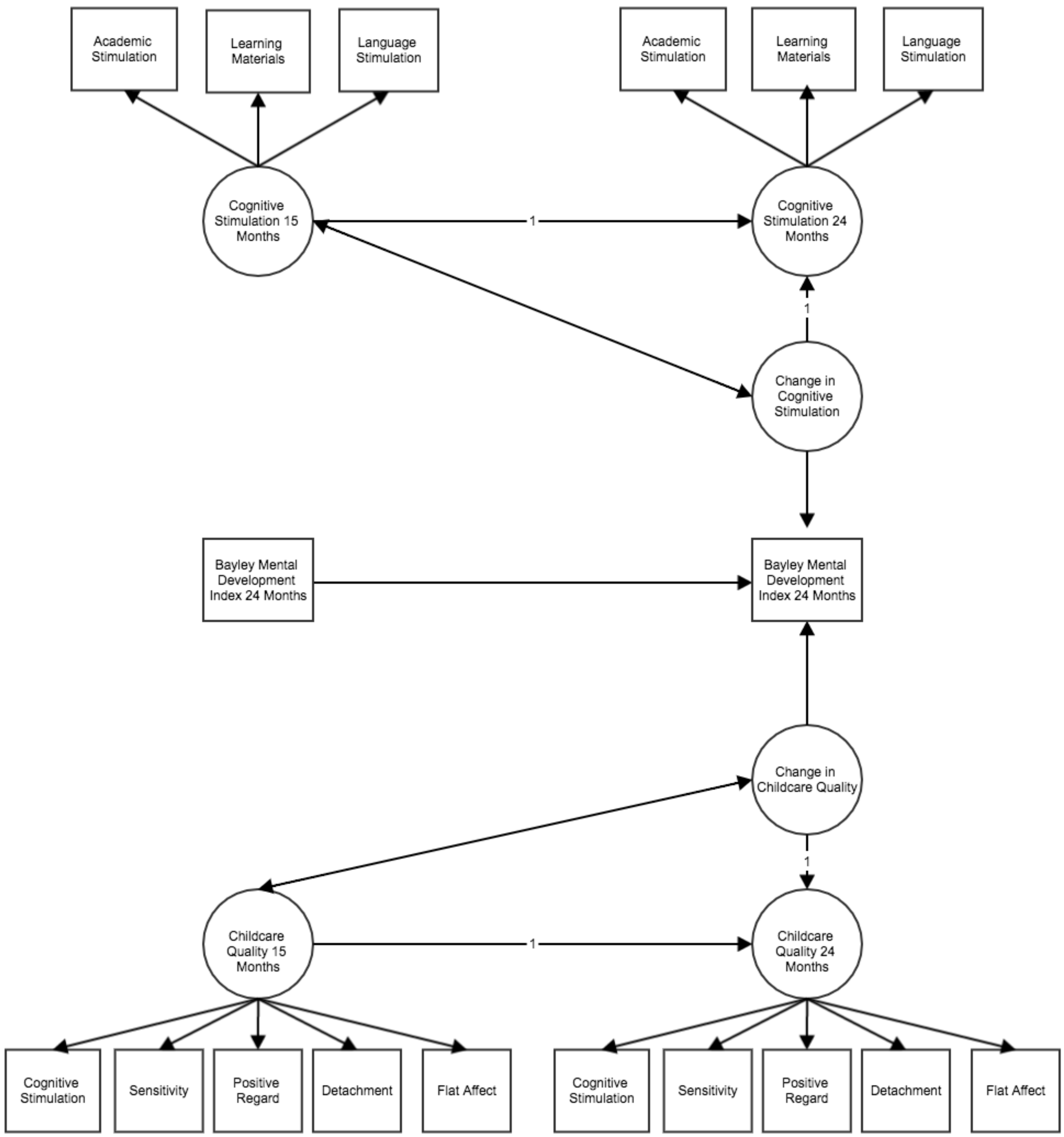


Figure 6. Depiction of Latent Difference Scores and Autoregression at the 15 and 24-month assessments.

Note. Income not drawn for ease of interpretation.

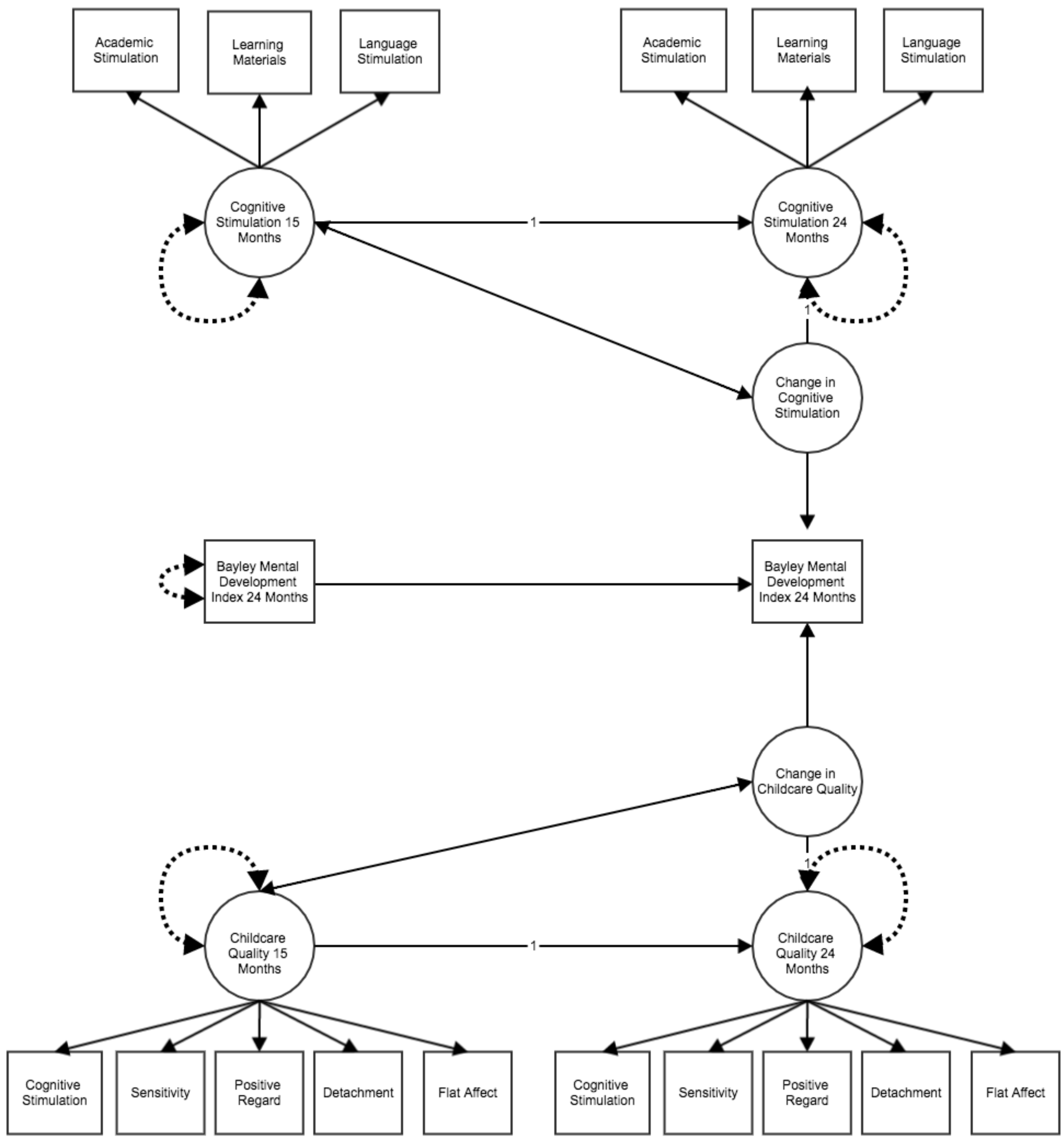


Figure 7. Step 1: First Order Factor Variances Constrained to Equality.

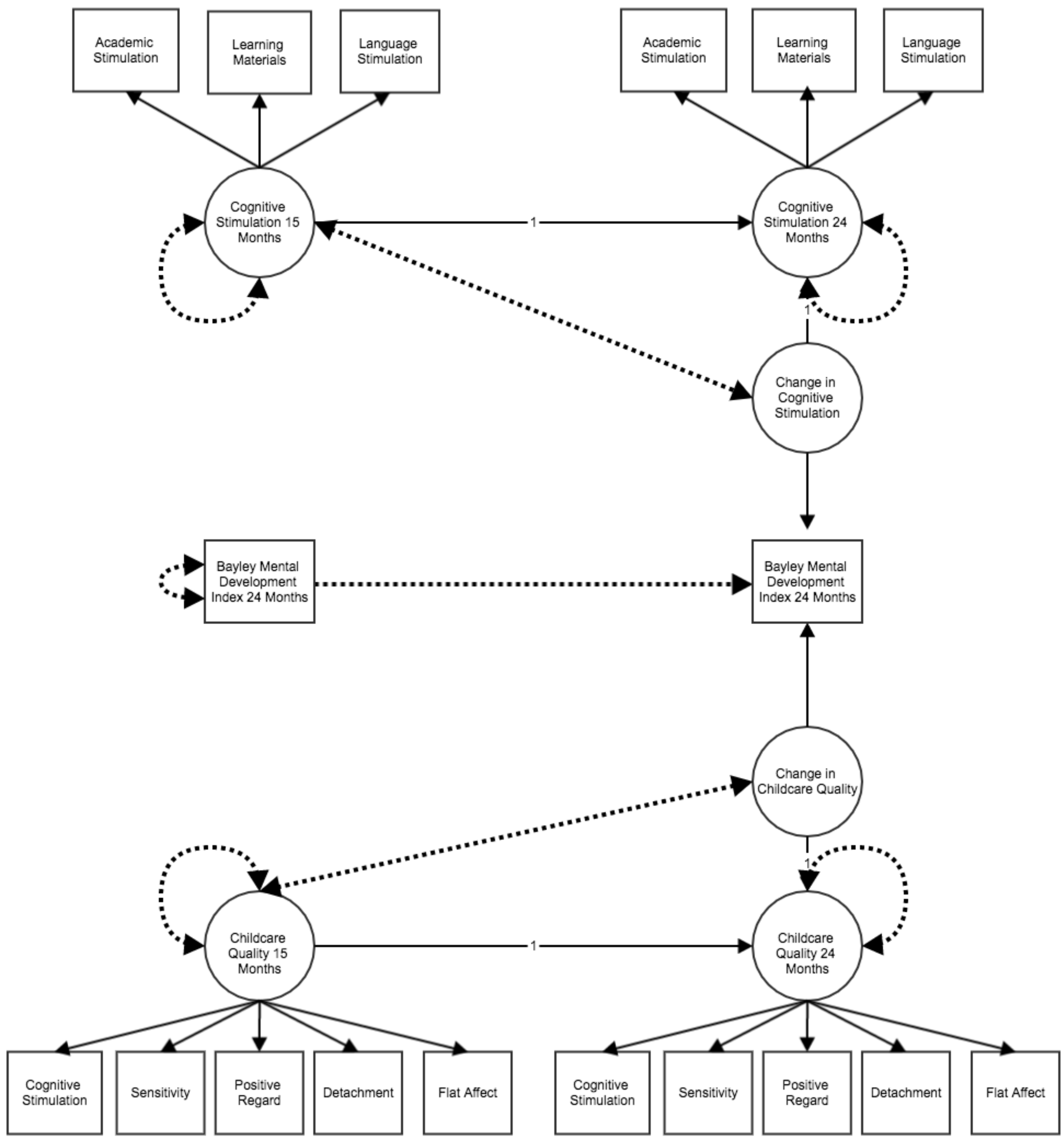


Figure 8. Auto-regressive parameters and covariances constrained to equality.

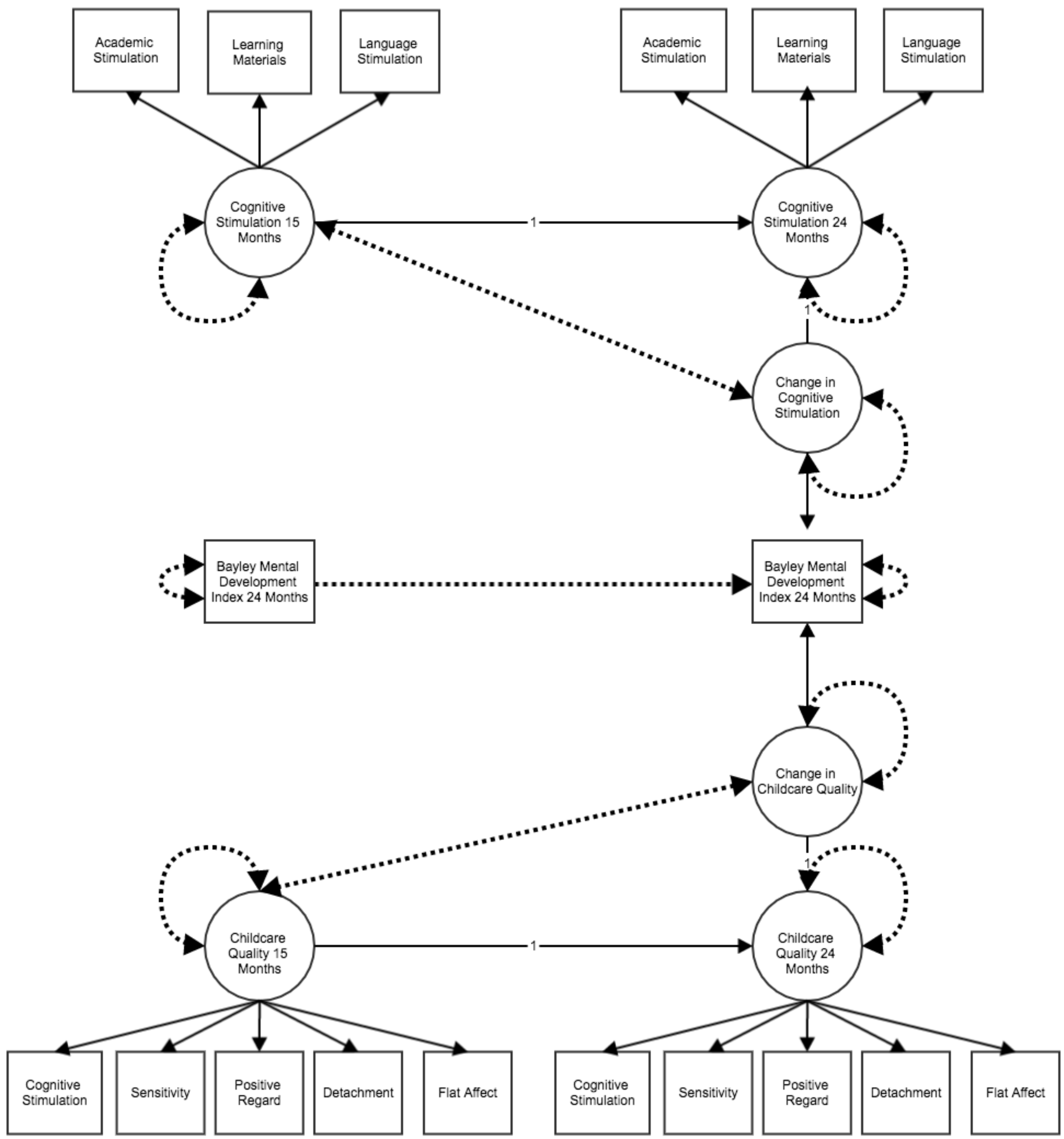


Figure 9. Second order factor variances and residual variances constrained to equality.

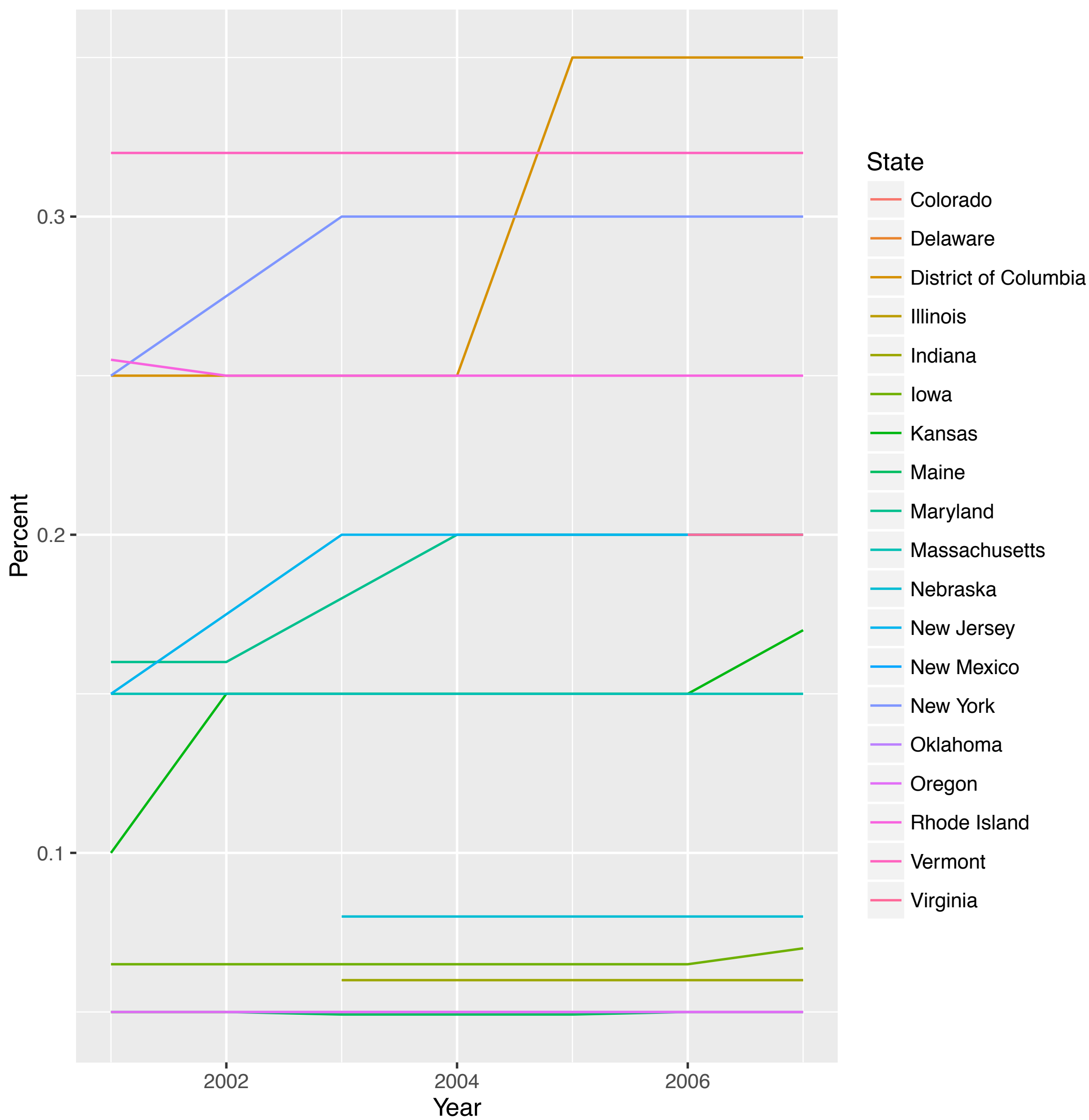


Figure 10. Variation in State EITC Over Time.

Note. States pay a percentage of federal EITC.

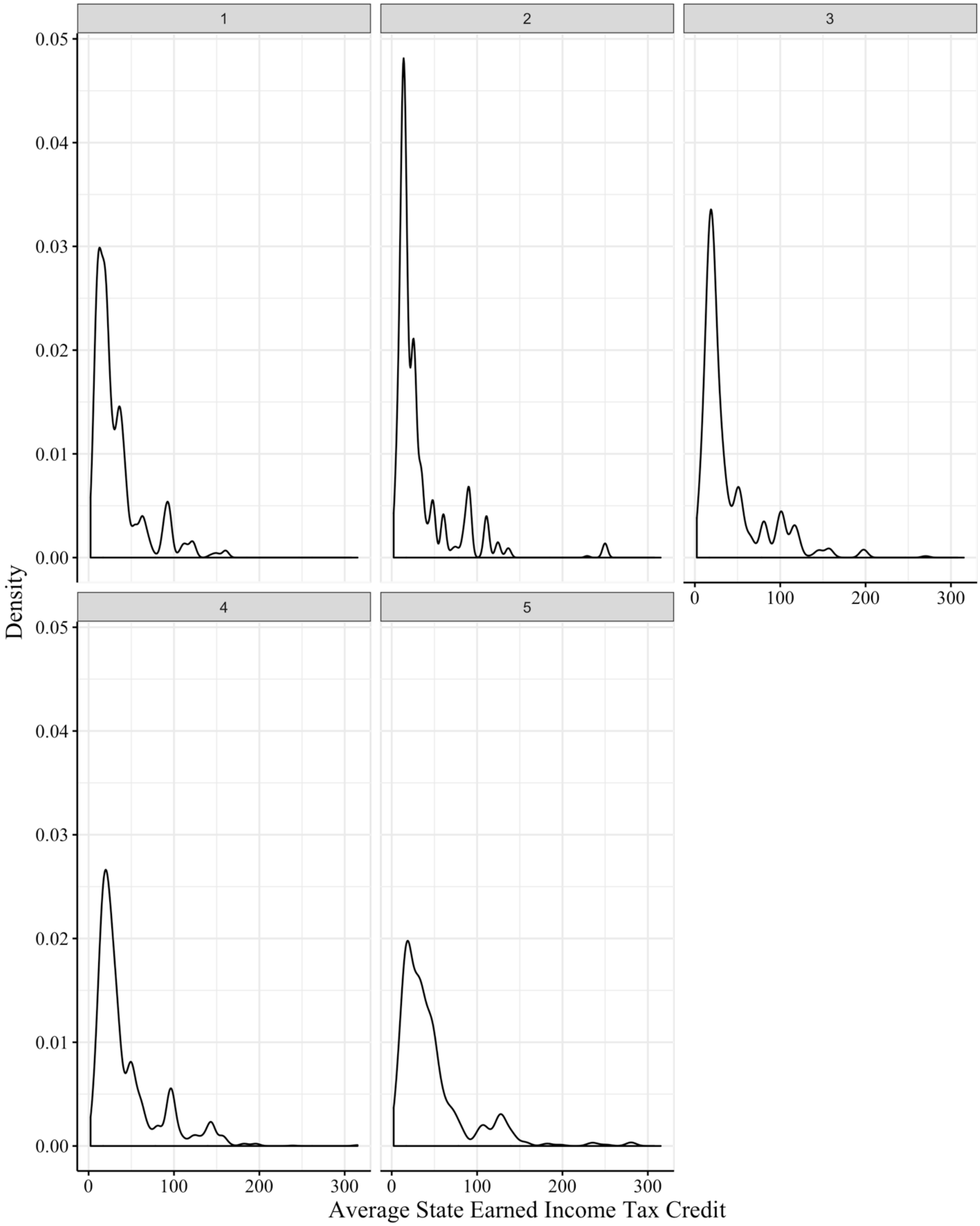


Figure 11. Variation in Average State EITC Over Time.

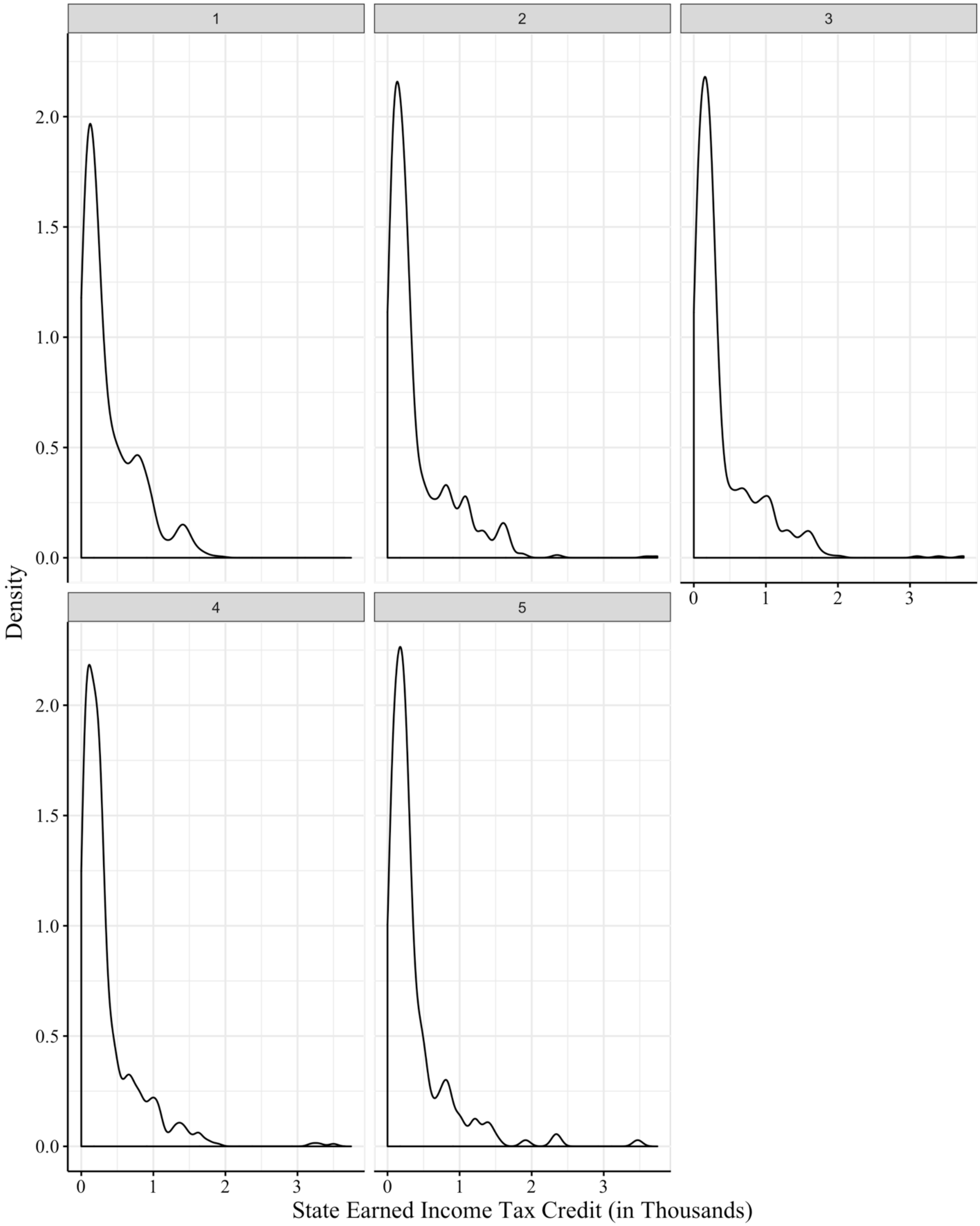


Figure 12. Variation in State EITC Over Time.

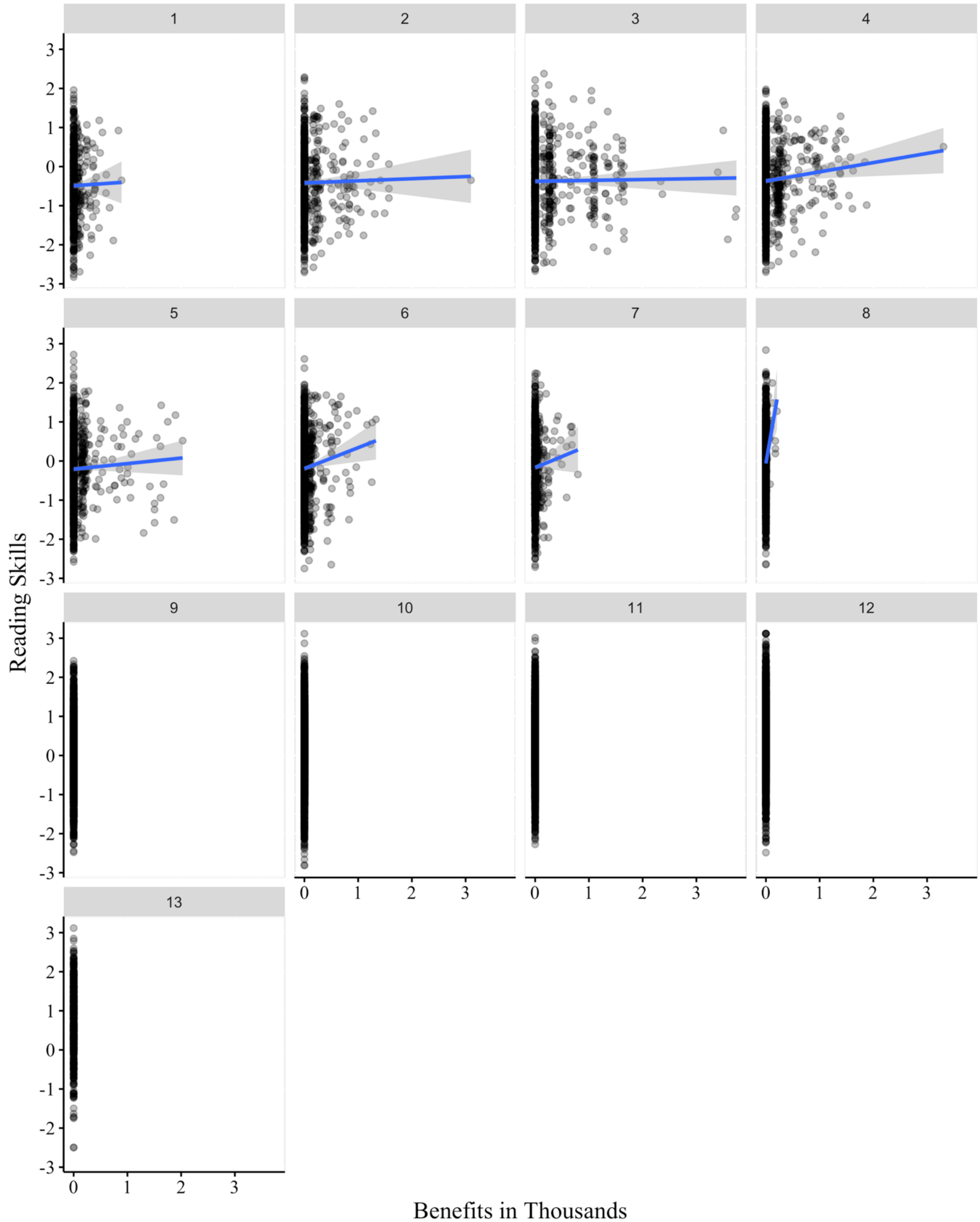


Figure 12. Effect of State Earned Income Tax Credit on Reading Skills.

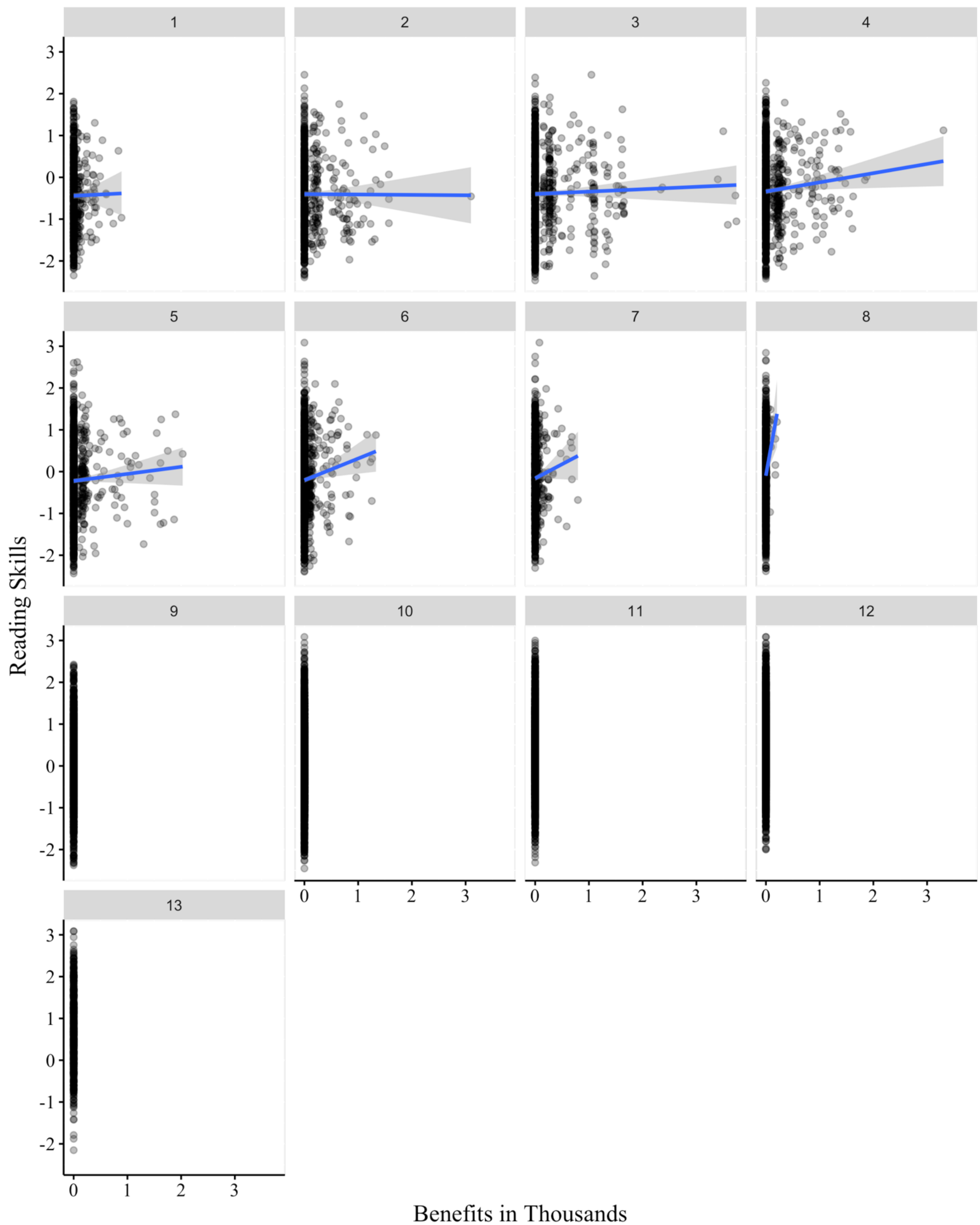


Figure 13. Effect of State Earned Income Tax Credit on Math Skills.

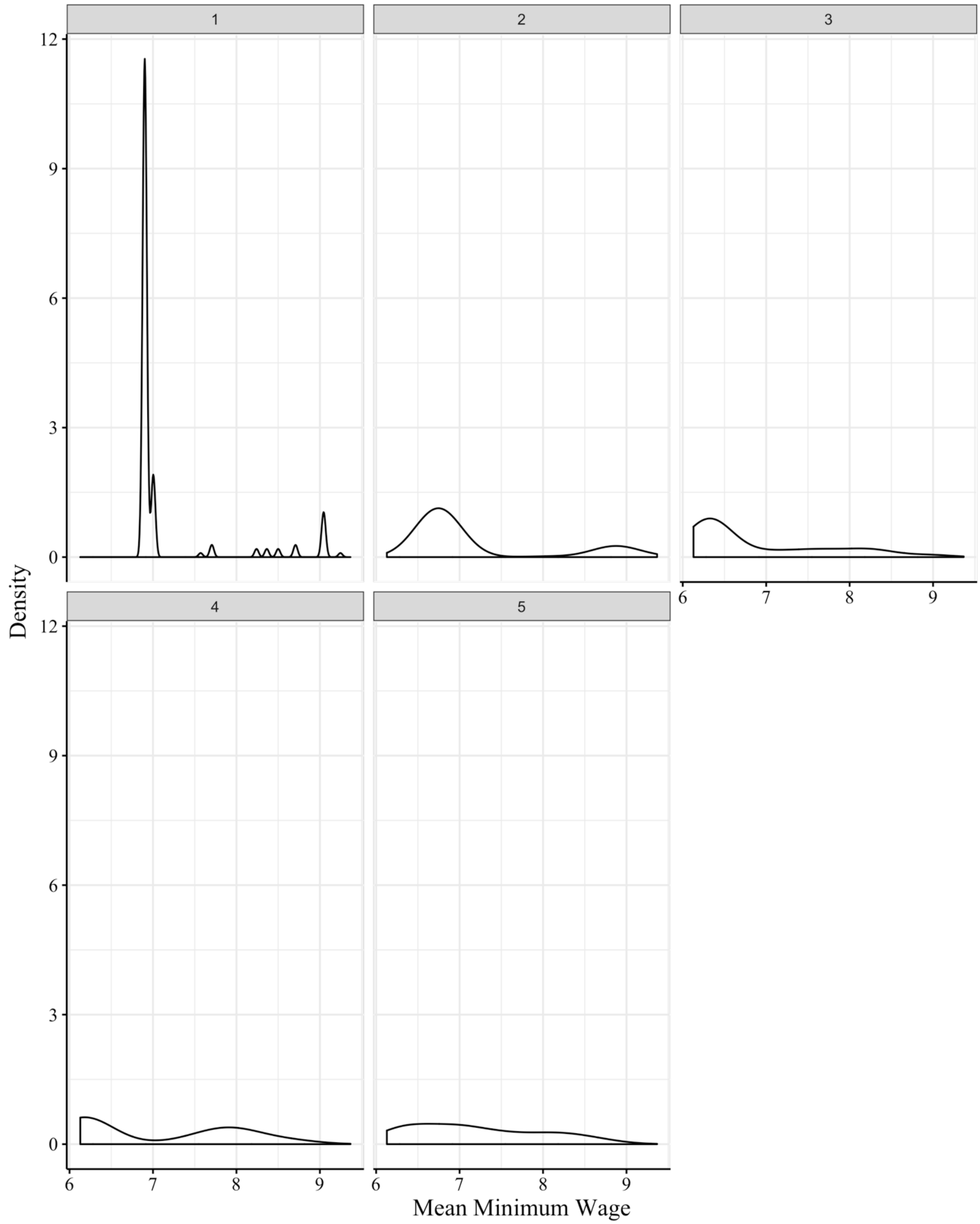


Figure 14. Variation in Mean Minimum Wage Over Time.

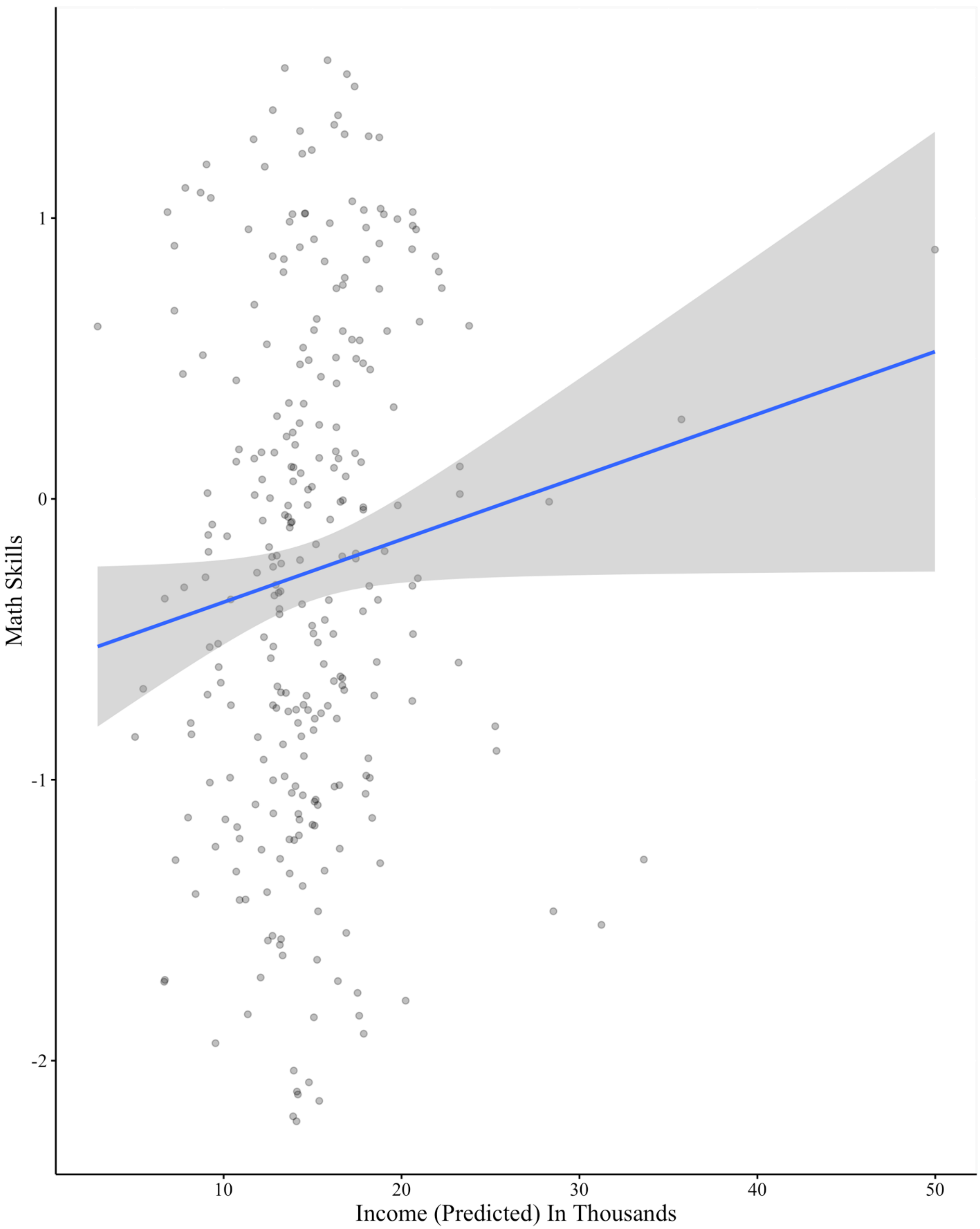


Figure 15. Effect of Second Stage Income on Math Skills.

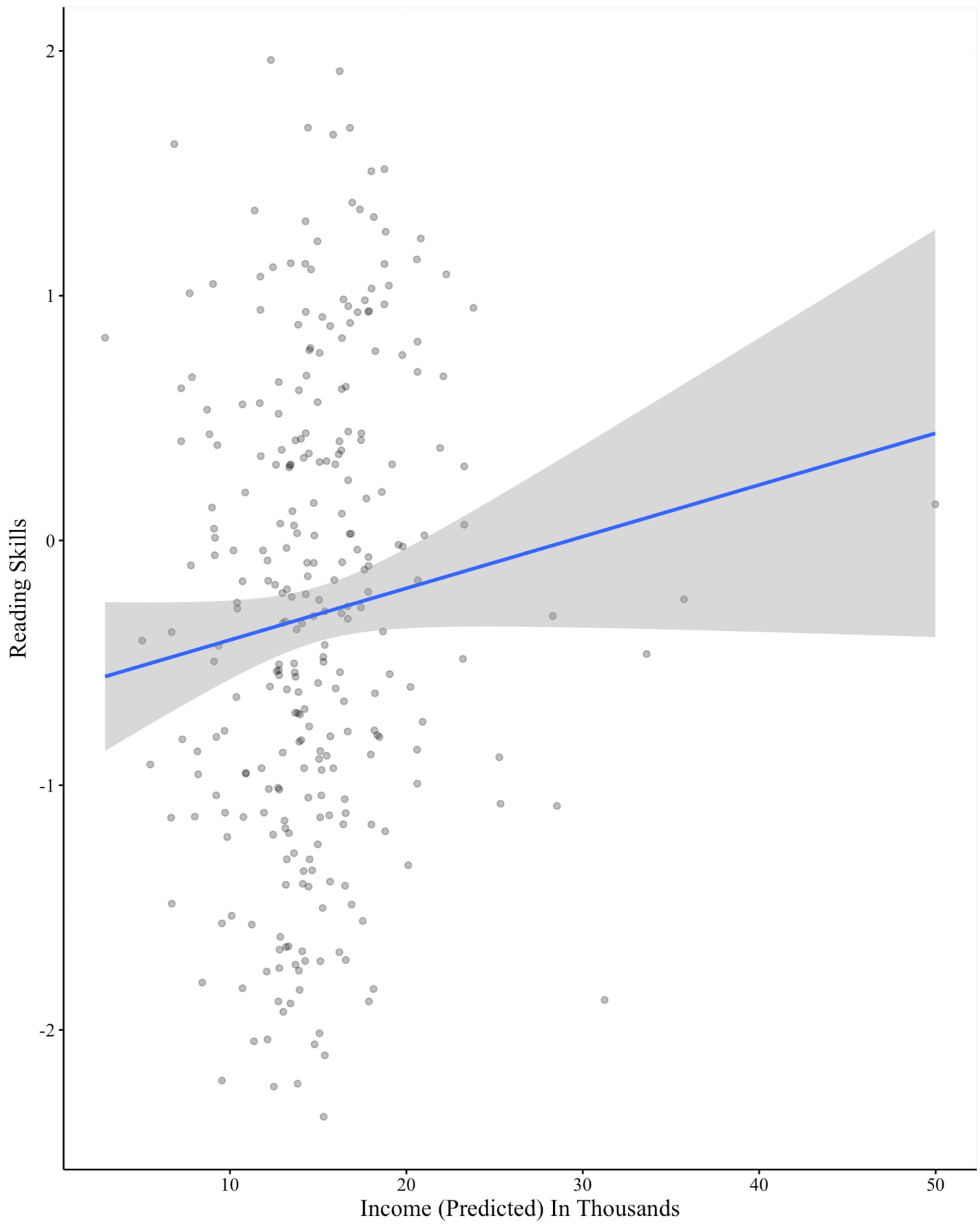


Figure 15. Effect of Second Stage Income on Reading Skills.

Tables

Table 1.

Measurement Framework for SECCYD

	Six Months	15 Months	24 Months	36 Months	54 Months
Cognitive Stimulation					
Academic Stimulation	X	X	X	X	X
Language Stimulation	X	X	X	X	X
Learning Materials	X	X	X	X	X
Childcare					
Cognitive Stimulation	X	X	X	X	X
Sensitivity	X	X	X	X	X
Positive Regard	X	X	X	X	
Detachment	X	X	X	X	X
Flat Affect	X	X	X	X	X
Responsivity					X
Intrusiveness					X
Fostering Exploration				X	
School readiness skills					
Mental Development Index		X	X		
Bracken Basic Concept				X	
Woodcock Johnson					X

Table 3.

Measurement Framework for ECLS-B

	Nine Months	Two Years	Four Years	Kindergarten
Cognitive Stimulation				
Maternal Reported Book Reading	X	X	X	X
Childcare Quality				
ITERS	X	X	X	X
FDCRS	X	X	X	X
School Readiness Skills				
Bayley Short Form	X	X		
Pre-CTOPPP			X	X
PPVT			X	X
TEMA-3			X	X
Items from FACES and ECLS-K			X	X

Table 4

Means, standard deviations, and correlations

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. WJ	97.23	11.43								
2. BBCS	8.81	2.90	.63**							
3. MDI	10.83	1.42	.41**	.32**						
4. Education	14.00	2.47	.43**	.42**	.12**					
5. ΔMarital$_{06-15}$	-0.01	0.21	-.01	.05	.02	.01				
6. ΔChildren$_{06-15}$	0.04	0.36	-.14**	-.09**	-.04	-.06	-.05			
7. ΔIncome$_{06-15}$	0.25	11.44	.00	-.00	-.05	.04	.19**	.03		
8. ΔHours$_{06-15}$	1.66	15.83	.03	-.02	-.03	-.02	-.02	-.05	.28**	
9. ΔDep.$_{06-16}$	0.01	7.60	-.01	-.03	.01	-.04	-.09**	-.03	-.02	.

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively. WJ = Woodcock Johnson; BBCS = Bracken Basic Concept Scale; MDI = Bayley Mental Development Index; Dep = Maternal Depression

Table 5

Participant Descriptive Statistics.

Variable	N	Percent
White	4032	0.42
Black	1483	0.15
Hispanic	1942	0.2
Asian	1095	0.11
Pacific Islander	42	0
Native American	237	0.02
More Than One	753	0.08
Male	4928	0.51
Female	4674	0.49
Married	6358	0.66
Single	3244	0.34
Exact Income	2134	0.22
Mean of Range	7468	0.78

Table 6

Total N Per Wave

Wave	N
1	9602
2	8644
3	7858
4	5586
5	1548

Table 7

Subsidy Use at Each Wave.

Wave	Subsidy Use (1 = Use)	N	Percent
1	0	9154	95
1	1	448	5
2	0	8036	93
2	1	608	7
3	0	6805	88
3	1	888	12
4	0	5301	98
4	1	123	2
5	0	1548	100

Table 8

Participant Descriptive Statistics: Childcare Sample

Variable	N	Percent
White	626	0.48
Black	324	0.25
Hispanic	217	0.17
Asian	35	0.03
Pacific Islander	4	0
Native American	9	0.01
More Than One	95	0.07
Male	659	0.5
Female	654	0.5
Married	816	0.62
Single	497	0.38
Exact Income	278	0.21
Mean of Range	1035	0.79

Table 9

Total N Per Wave: Childcare Sample

Wave	N
2	1313
3	1598

Table 11

Subsidy Use at Each Wave. Childcare Sample.

Wave	Subsidy Use (1 = Use)	N	Percent
2	0	1060	81
2	1	253	19
3	0	1332	83
3	1	266	17

Table 12

Means, standard deviations, and correlations, Wave 1

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Income	69.00	64.12							
2. Hours	17.70	19.37	.17**						
3. Benefits	0.04	0.17	-.18**	-.07**					
4. Children	2.33	0.95	-.05**	-.08**	.06**				
5. Education	4.33	1.96	.57**	.16**	-.14**	-.13**			
6. Maternal Depression	10.24	17.21	.02*	.00	-.03**	.00	.06**		
7. Book Reading	2.70	1.03	.18**	-.02	-.03**	-.09**	.24**	.03**	
8. Bayley Mental Development	48.22	10.86	.04**	.04**	-.01	-.11**	.06**	-.02	.08**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 13

Means, standard deviations, and correlations, Wave 2

Variable	*M*	*SD*	1	2	3	4	5	6
1. Income	73.18	66.09						
2. Hours	19.21	19.49	.14**					
3. Benefits	0.04	0.19	-.18**	-.05**				
4. Children	2.40	0.94	-.05**	-.10**	.07**			
5. Education	4.43	1.94	.57**	.14**	-.14**	-.12**		
6. Book Reading	3.12	0.90	.26**	-.02*	-.07**	-.08**	.33**	
7. Bayley Mental Development	49.09	10.02	.23**	.06**	-.07**	-.12**	.27**	.27**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 14

Means, standard deviations, and correlations, Wave 3

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Income	77.56	69.01								
2. Hours	21.77	19.91	.10**							
3. Benefits	0.04	0.18	-.17**	-.03*						
4. Children	2.59	0.90	-.03**	-.14**	.03**					
5. Education	4.61	1.94	.57**	.13**	-.13**	-.10**				
6. Maternal Depression	10.06	20.90	-.03*	-.01	-.01	.00	.02			
7. Book Reading	3.07	0.86	.27**	-.04**	-.04**	-.06**	.34**	.00		
8. Reading Skills	-0.48	0.76	.38**	.03**	-.07**	-.14**	.43**	-.05**	.28**	
9. Math Skills	-0.47	0.81	.37**	.06**	-.07**	-.12**	.40**	-.05**	.23**	.78**

Note. * indicates p < .05; ** indicates p < .01. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 15

Means, standard deviations, and correlations, Wave 4

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Income	82.07	69.64								
2. Hours	23.25	19.91	.08**							
3. Benefits	0.04	0.17	-.18**	-.02						
4. Children	2.65	0.89	-.04**	-.13**	.06**					
5. Education	4.73	1.96	.58**	.13**	-.15**	-.10**				
6. Maternal Depression	11.68	16.08	-.05**	-.00	.01	.04**	.01			
7. Book Reading	3.11	0.84	.25**	-.07**	-.06**	-.06**	.28**	-.03*		
8. Reading Skills	0.37	0.89	.35**	.07**	-.09**	-.15**	.37**	-.08**	.22**	
9. Math Skills	0.39	0.84	.37**	.08**	-.09**	-.13**	.39**	-.09**	.22**	.82**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 16

Means, standard deviations, and correlations, Wave 5

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. Income	80.04	69.63								
2. Hours	23.28	19.80	.08**							
3. Benefits	0.05	0.20	-.20**	-.03						
4. Children	2.70	0.88	-.01	-.15**	.03					
5. Education	4.68	1.91	.58**	.15**	-.14**	-.07**				
6. Maternal Depression	12.41	13.72	-.02	.01	-.08**	-.00	.02			
7. Book Reading	3.12	0.83	.20**	-.07**	-.06*	-.05	.23**	.01		
8. Reading Skills	0.91	0.75	.36**	.06*	-.11**	-.08**	.38**	-.03	.22**	
9. Math Skills	0.88	0.78	.41**	.08**	-.11**	-.06*	.43**	-.03	.20**	.81**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 17

Means, standard deviations, and correlations, Childcare Sample, Wave 2

Variable	*M*	*SD*	1	2	3	4	5	6
1. Income	77.61	68.12						
2. Hours	32.50	15.62	.21**					
3. Benefits	0.04	0.17	-.19**	-.10**				
4. Children	2.20	0.88	-.11**	.01	.06*			
5. Education	4.75	1.82	.59**	.15**	-.15**	-.14**		
6. Book Reading	3.15	0.89	.29**	.05	-.02	-.15**	.33**	
7. Bayley Mental Development	50.85	9.99	.26**	.10**	-.03	-.13**	.29**	.32**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 18

Means, standard deviations, and correlations, Childcare Sample, Wave 3

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Income	77.56	69.01									
2. Hours	21.77	19.91	.10**								
3. Benefits	0.04	0.18	-.17**	-.03*							
4. Children	2.59	0.90	-.03**	-.14**	.03**						
5. Education	4.61	1.94	.57**	.13**	-.13**	-.10**					
6. Maternal Depression	10.06	20.90	-.03*	-.01	-.01	.00	.02				
7. Book Reading	3.10	0.86	.27**	-.04**	-.04**	-.06**	.34**	.00			
8. Childcare Quality	0.02	0.72	.29**	-.04**	-.06**	-.02	.35**	.02	.79**		
9. Reading Skills	-0.44	0.76	.38**	.03**	-.07**	-.14**	.43**	-.05**	.28**	.28**	
10. Math Skills	-0.43	0.81	.37**	.06**	-.07**	-.12**	.40**	-.05**	.23**	.23**	[illegible]

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 19

Main Effects Estimates

	Unweighted		Weighted			
Variable	Est.	*t*	Est.	*t*	N	Total N
School Readiness Skills						
Bayley Mental Development Index	-.10	-0.14 (*p*)	-.13	-.178 (*p*)	8359	8903
Math Skills	.06	1.91	.07	2.09	7967	8498
Reading Skills	.10	2.77	.13	3.20	7968	8499
Cognitive Stimulation						
Book Reading	.01	0.29	-.03	-0.89	9350	9789
Childcare						
Parent Vs. All	-.65%	-0.29	-.62%	.220	9214	9697
Head Start Vs. All	-.66%	-0.53	3.38%	1.36	9214	9697
Center Vs. All	.57%	.251	-3.31%	-1.36	9214	9697
Other Vs. All	-.37%	-0.16	-.67%	-0.27	9214	9697
Childcare Quality	.13	1.17	.10	0.87	2303	2442

Table 20

Race/Ethnicity Moderation Benefits.

	Unweighted		Weighted			
Variable	Est.	*t*	Est.	*t*	N	
School Readiness Skills						
Math Skills: White	.07	1.18	.16	2.66	7967	8498
Math Skills: Black	-.14	-1.45	-.30	-3.30	7967	8498
Math Skills: Hispanic	.08	0.88	.04	0.46	7967	8498
Math Skills: Asian	.04	0.35	-.27	-1.49	7967	8498
Math Skills: Native Hawaiian	.66	1.07	.40	.56	7967	8498
Math Skills: Native American	-.01	-.08	-.18	-0.88	7967	8498
Math Skills: More Than One	-.01	-.13	-.07	0.12	7967	8498
Reading Skills: White	.22	3.53	.30	4.85	7968	8499
Reading Skills: Black	-.30	-3.15	-.40	-4.30	7968	8499
Reading Skills: Hispanic	-.15	-1.64	-.18	-1.94	7968	8499
Reading Skills: Asian	-.13	-1.09	-.35	1.80	7968	8499
Reading Skills: Native Hawaiian	.43	0.66	.51	.65	7968	8499
Reading Skills: Native American	-.06	-0.49	-.24	-1.04	7968	8499
Reading Skills: More Than One	-.09	-0.74	-.18	-1.40	7968	8499

Table 21

Participant Descriptive Statistics

Variable	N	Percent
White	46	28
Black	59	35
Hispanic	35	21
Asian	8	5
Native American	7	4
More Than One	12	7
Male	78	47
Female	89	53
Married	46	28
Single	121	72

Table 22

Total N Per Wave

Wave	N
1	167
2	156
3	167
4	110
5	40

Table 23

Subsidy Use at Each Wave.

Wave	Subsidy Use (1 = Use)	N	Percent
1	0	134	80
1	1	33	20
2	0	117	75
2	1	39	25
3	0	125	75
3	1	38	23
4	0	98	89
4	1	1	1
5	0	40	100

Table 24

Means, standard deviations, and correlations, Wave 1

Variable	*M*	*SD*	1	2	3	4	5	6
1. Income	14.23	3.70						
2. Hours	37.53	8.82	.86**					
3. Children	2.16	1.23	.08	.06				
4. Education	3.17	1.28	-.01	.06	-.10			
5. Maternal Depression	13.69	7.17	.07	.15	.16	.14		
6. Book Reading	2.44	0.99	-.19*	-.16*	-.08	.17*	.03	
7. Bayley Mental Development	47.60	9.70	.07	.09	-.08	.15*	.10	-.02

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 25

Means, standard deviations, and correlations, Wave 2

Variable	*M*	*SD*	1	2	3	4	5
1. Income	13.96	3.96					
2. Hours	36.82	8.60	.84**				
3. Children	2.20	1.10	.07	.11			
4. Education	3.16	1.22	-.00	.07	-.20*		
5. Book Reading	2.74	0.92	.03	.11	.15	.08	
6. Bayley Mental Development	44.08	21.92	-.05	.01	-.05	.00	.10

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 26

Means, standard deviations, and correlations, Wave 3

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Income	14.34	4.45							
2. Hours	39.23	10.22	.85**						
3. Children	2.45	1.25	.03	.03					
4. Education	3.45	1.41	.13	.10	-.08				
5. Maternal Depression	15.99	5.71	-.06	-.07	.00	.01			
6. Book Reading	2.71	0.83	.10	.11	-.05	.25**	-.02		
7. Reading Skills	-0.85	0.69	.05	-.02	-.15	.14	.05	-.06	
8. Math Skills	-0.78	0.66	-.02	-.02	-.07	.06	.03	-.05	.74**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 27

Means, standard deviations, and correlations, Wave 4

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Income	15.48	4.37							
2. Hours	39.62	8.84	.88**						
3. Children	2.70	1.26	.33*	.21					
4. Education	3.77	1.44	.13	.33*	-.04				
5. Maternal Depression	16.68	5.43	.03	-.00	-.03	.02			
6. Book Reading	2.88	0.85	-.19	-.17	-.06	-.25	-.13		
7. Reading Skills	0.64	0.70	.01	-.05	-.09	.01	-.11	-.14	
8. Math Skills	0.64	0.76	-.06	-.16	-.07	.02	-.07	-.14	.78**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 28

Means, standard deviations, and correlations, Wave 5

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Income	15.46	5.33							
2. Hours	41.45	12.22	.85**						
3. Children	2.46	1.28	.07	.04					
4. Education	3.15	1.27	.14	.13	-.21*				
5. Maternal Depression	16.25	6.97	-.07	-.02	.16	-.03			
6. Book Reading	2.85	0.88	.09	-.00	-.08	.19	-.01		
7. Reading Skills	0.12	0.84	.04	-.05	-.09	.16	-.14	.18	
8. Math Skills	0.12	0.79	.13	.04	-.09	.15	-.19	.23*	.84**

Note. * indicates $p < .05$; ** indicates $p < .01$. *M* and *SD* are used to represent mean and standard deviation, respectively.

Table 29
Minimum Wage Estimates.

	Unweighted		Weighted			
Variable	Est.	P	Est.	P	N	Total N
School Readiness Skills						
Bayley Mental Development Index	-3.59	.989	-3.30	.883	296	300
Math Skills	.05	.055	.05	.081	263	280
Reading Skills	.09	.003	.10	.004	264	281
Cognitive Stimulation						
Book Reading	-.02	.800	.10	.100	532	548
Childcare						
Parent Vs. All	16.47%	.001	4.01%	.012	435	445
Head Start Vs. All	-3.23%	<.001	-2.69%	<.001	435	445
Center Vs. All	<.001%	.964	<.001%	.972	435	445
Other Vs. All	3.00%	.012	-2.65%	.121	435	445

Table 30
Race/Ethnicity Moderation Income

	Unweighted		Weighted			
Variable	Est.	P	Est.	P	N	Total N
School Readiness Skills						
Math Skills: White	.04	.244	.03	.452	263	280
Math Skills: Black	.02	.238	.02	.228	263	280
Math Skills: Hispanic	.03	.105	.04	.056	263	280
Math Skills: Asian	.07	.132	.04	.569	263	280
Math Skills: Native American	.05	.199	.05	.308	263	280
Math Skills: More Than One	.10	<.001	.12	<.001	263	280
Reading Skills: White	.08	.320	.06	.512	264	281
Reading Skills: Black	-.007	.708	.008	.656	264	281
Reading Skills: Hispanic	.03	.109	.06	.008	264	281
Reading Skills: Asian	.11	.032	.07	.286	264	281
Reading Skills: Native American	-.04	.367	-.02	.695	264	281
Reading Skills: More Than One	.05	.108	.08	.024	264	281