Changing Circumstances, Changing Outcomes? Longitudinal Relations Between Family Income, Cumulative Risk Exposure, And Children's Educational Success

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CHANGING CIRCUMSTANCES, CHANGING OUTCOMES? LONGITUDINAL RELATIONS BETWEEN FAMILY INCOME, CUMULATIVE RISK EXPOSURE, AND CHILDREN'S EDUCATIONAL SUCCESS

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ABSTRACT

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Emerging research in developmental psychology and neuroscience suggests that childhood poverty is associated with high levels of exposure to multiple contextual risks, which cumulatively lead to persistent elevated stress levels that have a direct, as well an indirect (e.g., through parental processes), impact on child cognitive, academic, and socioemotional functioning (Evans & Kim, 2013). Such research has begun to change the way that scholars and practitioners envision the context of poverty, the persistence of the income-achievement gap, and the types of interventions that may be most effective in addressing disparities in children's long-term educational success. However, research on the relations between poverty-associated stress and child outcomes is still in its infancy and many questions remain. In particular, it is unclear whether changing family economic circumstances matter, a question of concern for developmental science and public policy. Moreover, there is little work on moderators of relations between income, stress, and child outcomes, which could help identify factors that buffer children from the harm of stressful home environments.

With longitudinal data from the Panel Study of Income Dynamics' Child Development Supplement, the present study used fixed effects models to examine within-child associations between changes in family income, cumulative risk exposure (as

measured by an index that includes a range of poverty-related stressors, such as economic strain, neighborhood crime, and physical and psychological home environments), and children's cognitive, academic and socioemotional functioning. In addition, moderators of these associations were investigated in order to identify potential protective mechanisms and crucial levers for interventions and policy development. On the whole, findings were consistent with the cumulative stress model. On average, the estimated direct effects of changes in family income (i.e., prior to examining mediation or moderators) were not significant for changes in child outcomes. Yet, changes in income were, for the sample as a whole, indirectly related via changes in cumulative risk exposure: increases in income predicted decreases in cumulative risk exposure which, in turn, predicted improvements in achievement and declines in externalizing behavior. Additionally, these relations were moderated by child age, initial level of family income, and initial level of cumulative risk.

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CHAPTER 1: INTRODUCTION

Over the past four decades, income disparities in the United States have substantially widened, with household incomes among those in the first through fourth quintiles rising a mere 0.45 percent per year (an extra $2 per week for a household with an income of $25,000), while household incomes in the top quintile rose three times as fast at 1.35 percent per year (an extra $25 per week for a household with an income of $100,000; Congressional Budget Office, 2014). Along with this increasing income gap between the rich and the poor, disparities between children from low- and high-income families also grew significantly larger on a range of academic outcomes, from mathematics and reading achievement (Reardon, 2011) to college completion (Bailey & Dynarski, 2011). Using data from nineteen nationally representative studies, Reardon (2011) estimated that the achievement gap between students whose family income was at or above the 90^{th} percentile and those whose family income was in the bottom 10^{th} percentile grew about 40%, from a difference of 0.75 of a standard deviation in 1970 to a difference of 1.25 standard deviations in 2001. Although recent estimates indicate a small narrowing, the achievement gap between the richest (90^{th} percentile) and poorest (10^{th} percentile) remains wide, similar to what we would expect from four additional years of schooling (Reardon, 2011; Reardon et al., 2016), and would still take 60-100 years to fully close at the current rate.

Gaps between high- and low-income children with respect to socioemotional and behavioral skills appear smaller than those for achievement – a recent study by the Economic Policy Institute estimated differences between low and high-income students prior to school entry to be 0.16 of a standard deviation for internalizing behaviors and 0.19 of a standard deviation for externalizing behaviors (Garcia, 2015) – but the personal and social costs of maladjustment in these areas due to economic disadvantage may be tremendous (Dearing, McCartney, & Taylor, 2006). These costs are, in part, a function of the fact that socioemotional adjustment is significantly related to children's school readiness, educational attainment, and crime and socioeconomic success in adulthood, over and above cognitive ability (see Duncan & Magnuson, 2011; Farkas, 2011; Heckman, 2008; Heckman & Kautz, 2012). Moreover, children's social and behavioral skills likely support and interact with cognitive abilities: that is, children with better social and behavioral skills tend to learn more than children with poor social and behavioral skills (Jennings & DiPrete, 2010). Indeed, Heckman and colleagues (Heckman, Moon, Pinto, Savelyev, & Yavitz, 2008) have argued that early intervention programs for children in poverty like the Perry Preschool Program have lasting effects – on school achievement, earnings, and delinquency in young adulthood – primarily through positive effects on children's early social and behavioral skills and the cascading consequences of these skills.

Across achievement and socioemotional domains, areas of exciting progress in the study of the developmental consequences of poverty have been centered on the mechanisms by which income impacts developmental outcomes, nuanced consideration of the dynamic aspects of family economic well-being, and efforts to move past correlations to probing causal hypotheses. Historically, research on the associations between family income and child development outcomes has been framed by two dominant theories that have emphasized the role of income on a child's access to cognitively stimulating resources or on a parent's mental health and parenting practices (Dearing, 2008; Gershoff, Aber, Raver, & Lennon, 2007; Linver, Brooks-Gunn, & Kohen, 2002; Yeung, Linver, & Brooks-Gunn, 2002). Over the last decade, however, there has been growing interest in a third, complementary mechanism: the cumulative risk pathway. Theoretical and empirical work on this pathway highlights the physiological effects of poverty-associated stress on a child's developing brain in explaining the associations between income and long-term child development outcomes. Gary Evans and colleagues (Evans & Kim, 2013; Evans & Schamberg, 2009), for example, have presented compelling evidence for the cumulative risk pathway, arguing that early childhood poverty often exposures children to multiple contextual risks, leading to chronically elevated stress levels and corresponding physiological effects that have a direct effect on child working memory, academic, and socioemotional functioning. Because it highlights the multipronged mechanisms of harm endemic to poverty and because it highlights the neurological underpinnings of this harm, research on the cumulative risk pathway has begun to change the way that scholars and practitioners envision the context of poverty, the stubborn persistence of the income-achievement gap, and the types of interventions that may be most effective in addressing the disparities in children's long-term success and well-being.

However, research on this relation between poverty-associated stress and child development is in a nascent stage and many pressing questions remain unanswered. As a case in point, few scholars studying links between poverty, stress, and child outcomes have attempted to capture the dynamic nature of these phenomena and their relations with one another. It is clear that income is often volatile, especially for lower-income households, with families falling into poverty and/or rising out of poverty, sometimes repeatedly (Dearing, McCartney, & Taylor, 2001; Duncan, 1988; Dynan, Elmendorf, & Sichel, 2007). Similarly, children's exposure to stress and risk is unlikely stable in many families. Stress and risk likely ebb and flow according to economic circumstances and other dynamic aspects of family life.

Consistent with this speculation, work on maternal depressive symptoms during the first three years of a child's life suggests considerable volatility and responsiveness to changing economic circumstances (Dearing, Taylor, & McCartney, 2004). Yet, parent mental health is only one isolated aspect of the risks to which children in poverty may be exposed. The extent to which cumulative risk is dynamic, and the extent to which any such dynamics are meaningful for children's development has received little attention to date. In addition, little attention has been given to factors that may exacerbate or mitigate relations between income, cumulative stress, and child outcomes; this work is critical for targeting interventions toward the most vulnerable children and the most promising means of promoting their growth.

The present study. Using longitudinal data from the Panel Study of Income Dynamics Child Development Supplement, the proposed dissertation examined within- and between-child associations between changes in family income, cumulative risk exposure (as measured by an index that includes a range of poverty-related stressors, such as economic strain, neighborhood crime, physical home environment, and intra-family violence), and child academic achievement and socioemotional functioning. In addition, potential moderators of these associations – such as level and developmental timing of income or risk and race/ethnicity – were investigated in order to identify potential protective mechanisms and key “levers” for interventions and policy development, as well as critical time periods and populations on which to focus such interventions and policies.

CHAPTER 2: LITERATURE REVIEW

How Poverty Influences Child Development: Prevailing Theoretical Models

Two main theories have dominated the field with respect to the mechanisms underlying the associations between family income and child developmental outcomes, and both focus on the role of family as the primary mechanism through which poverty affects children. The Family Stress Model emphasizes the role of income-dependent economic pressures on parental mental health, family relationships, and parenting behaviors in mediating the associations between income and child socioemotional functioning (Conger et al., 1994; Conger et al., 2002). Specifically, this model is focused on the ways in which economic hardship increases parenting stress and inter-parental conflict, thereby impairing parental mental health (e.g., increased depressive symptoms) and, in turn, increasing the likelihood that parenting is harsh and inconsistent, all of which put children at risk for socioemotional disregulation (Conger & Conger, 2002). Considerable evidence over the past few decades has provided support for the Family Stress Model across a range of ethnic, geographic, and family structure variations (Conger et al., 2002; Linver, Brooks-Gunn, & Kohen, 2002; Mistry, Vandewater, Huston, & McLoyd, 2002; Parke et al., 2003; Yeung, Linver, & Brooks-Gunn, 2002).

Meanwhile, the Parental Investment Model highlights the relation between a family's economic resources and the ability to invest both time and money in cognitively stimulating resources and activities for their children, fundamental aspects of the home environment affecting cognitive and achievement outcomes (Becker & Tomes, 1994). Developed within the economics literature, the primary proposition of the Family Investment Model is that economic resources constrained families' propensities to invest in their children such that lower-income parents will prioritize their family's more proximal, short-term survival needs (e.g., food, housing, and clothing) over learning investments in the long-term development of their children, such as financial expenditures on learning-related materials (e.g., books, puzzles, toys), time/energy investments in cognitively stimulating activities with their child (e.g., reading to their child, helping with homework), and investments that require both money and time/energy (e.g., trips to the museum). Work by researchers such as Smith and colleagues (1997) provide support for this model, finding that children in their nationally representative samples who lived in poverty scored significantly lower on various standardized achievement tests than children in families whose incomes were above the federal poverty line, and these differences were mediated by the ability of higher income families to provide educationally enriching materials and activities for their children.

A few studies (Gershoff et al., 2007; Linver et al., 2002; Yeung et al., 2002) have attempted to combine these models and examine predictions from both perspectives simultaneously. These studies generally support the idea that both pathways independently explain associations between family income and child outcomes with family stress explaining links between poverty and socioemotional dysfunction and family investments explaining links between poverty and cognitive outcomes. Yeung and colleagues (2002) found that together, family stress and parent investments explained approximately half of the association between income and child outcomes, supporting the theory that most of the effects of family income are likely indirect, transmitted to children through family processes, such as parenting behavior and investments. However, new developments in neuropsychology have led researchers such as Evans and Kim (2013) to propose a third, complementary pathway for understanding the impacts of family income on children, namely the cumulative risk pathway.

The Cumulative Risk Model: A Third Complementary Pathway

Evans and Kim's (2013) cumulative risk model, sometimes also referred to as the risk-stress model, highlights the neurobiological effects of stress on children's developing brains due to cumulative (additive) and/or chronic (over time) exposure to the wide array of contextual risk factors, both inside and outside of the home, that accompany poverty. Within the home, children growing up in low-income families are more likely to experience environments that are more disorganized, unpredictable, and unsafe: their homes may be characterized, for example, by overcrowding, the presence of lead paint and other toxins, health problems, marital conflict, physical violence, and/or family instability (Conger, Conger, & Martin, 2010; Evans, 2004; Margolin & Gordis, 2004; Vernon-Feagans, Garrett-Peters, DeMarco, & Bratsch-Hines, 2012). These same children are also more likely to experience physical and psychological stressors outside of the home, such as deteriorated community buildings, inadequate access to services and safe places for children to play, residential turnover and weak social ties or support systems, and greater incidence of crime and violence (Cradock et al., 2005; Sampson et al., 2002). The presence of such stressors affect children's ability to feel safe in their environments and require their physiological stress response systems to repeatedly react and adapt to precarious, unpredictable, and threatening situations (Repetti, Taylor, & Seeman, 2002; Repetti, Wang, & Saxbe, 2009), thereby altering the levels of stress hormones, such as cortisol, that regulate synaptic activity in brains areas related to attention, spatial learning, working memory, and regulation of emotion (Blair, Berry, et al., 2013; Blair, Raver, Granger, Mills-Koonce, & Hibel, 2011; Chen, Cohen, & Miller, 2010; Evans, 2003; McEwen, 2006). In this way, cumulative exposure to multiple contextual risks and the resulting physiological stress are thought to mediate the association between income and child cognitive and socioemotional functioning.

Key to the cumulative risk model is the recognition and identification of the multiplicity of contextual risk factors that accompany poverty, as highlighted in seminal research by McLoyd (1998) and Evans (2004). Both McLoyd's and Evans' research is rooted in a bioecological (Bronfenbrenner, 1986; Bronfenbrenner & Morris, 2006) model of development, which emphasizes not only the complex, mutually influential relationship between a child and its immediate environment, such as the family, but also the ways in which this more proximal environment is, in turn, shaped by broader environments, such as the community in which the family lives, the larger society in which that community finds itself, and even the given period in history. In this same vein, while a long tradition of research on the environment of childhood poverty has focused on the way in which a family's income is linked to child outcomes indirectly through parenting decisions and behavior, McLoyd (1998) and Evans (2004) argue that the family is but one of a range of contexts through which poverty makes its mark on children's lives. To be sure, parenting and family processes are critical components of children's most proximal environments, their psychological home environments (Duncan, Ludwig, & Magnuson, 2010), but these may be just one of the social and physical milieu contributing an array of stressors that accumulate in the lives of poor children. Poverty also influences child development through its relations with the physical conditions of the home and neighborhood as well as the accessibility to, and quality of, developmentally relevant resources and relationships outside the home (e.g., early childhood education and care, community services, schools; McLoyd, 1998; Evans, 2004).

The biological underpinnings of the cumulative risk model. A growing number of studies have begun to explore mechanisms, such as heightened stress levels, that have been theoretically posited to explain how poverty-associated cumulative risk may influence child cognitive, academic, and socioemotional functioning. In particular, recent research has examined the relation between exposure to multiple contextual risks and physiological markers indicative of stress levels. Gunnar and colleagues (Gunnar & Donzella, 2002; Gunnar & Quevedo, 2007; Gunnar & Vasquez, 2001), for example, have found that levels of the stress hormone cortisol can be powerfully influenced by early social and environmental experiences. More specifically, chronic exposure to stressful contexts may result in an overactive HPA system that is constantly producing high levels of cortisol in order to mobilize all the body's resources to have the energy to effectively cope with potential threats. For instance, Karb, Elliott, Dowd, and Morenoff (2012) found that adults with high levels of perceived and observed neighborhood stressors tended to have higher cortisol levels over the course of the day. Blair and colleagues (2011, 2013) found a similar pattern in children, with those experiencing unstable and chaotic environments more likely to have higher levels of resting cortisol at 7 through 48 months of age. These authors also found that children with more cumulative time in poverty and those with more cumulative exposure to household chaos have higher cortisol levels than other children (Blair, Berry, et al., 2013). While other studies may not have specifically looked at the association between exposure to stressful or chaotic contexts and stress physiology, a handful have found a relationship between poverty itself and higher cortisol levels in young children (see, e.g., Lupien et al., 2001).

Limited research has also explored the associations between high cortisol levels – and children's cognitive and social-emotional problems (Gunnar & Vasquez, 2001). In addition to mobilizing our body's resources to deal with potential threats, cortisol modulates activity in brain areas, such as the prefrontal cortex, hippocampus, and amygdala, which support memory, executive function skills, spatial learning and emotional regulation. Under mild stress conditions, moderate levels of cortisol seems to facilitate and sustain cognitive functioning; but chronically high or low levels of cortisol can have damaging effects on neuronal structures and may lead to impairments in a wide range of cognitive and emotional regulation processes (Arnsten, 2009; de Kloet, Ron, Oitzl, & Joëls, 1999; Erickson, Drevets, & Schulkin, 2003; Joëls & Baram, 2009; Lupien, McEwen, Gunnar, & Heim, 2009; Sapolski, 1999, 2003; Ulrich-Lai & Herman, 2009). Few studies thus far have examined the relation between cortisol levels and cognitive and emotional functioning in children, but those that have support the animal and adult research upon which this model was based. Blair and colleagues (2011), for example, found that higher baseline cortisol levels in infancy were associated with lower performance on executive function tasks at age 3. Suor and colleagues (2015) found that elevated cortisol levels between the ages of 2 and 4 were associated with lower IQ scores at age 4, and Granger and colleagues (Granger, Stansbury, & Henker, 1994; Granger, Weisz, Ikeda, McCracken, & Douglas, 1996) found an association between high levels of cortisol and internalizing behaviors in preschool and school-age children.

Taken together, this research suggests that chronic exposure to multiple contextual risks may affect children's cognitive and socioemotional functioning through its effect on the body's physiological stress response system. In combination with the broader literature, this research provides compelling theoretical justification for further exploring the potentially critical role of cumulative exposure to multiple contextual risks in explaining the persistent association between poverty and child developmental outcomes.

What are the risk factors leading to accumulating stress in the context of poverty? According to the cumulative risk model, a key to understanding the consequences of poverty is the recognition that stress exposure is multi-pronged for poor children, and it is the accumulation of stress exposure (across home and out-of-home contexts) that creates exceptionally pernicious developmental consequences. Of particular interest among researchers studying the cumulative risk model, including the present research, are psychosocial and physical stressors for which there are both theoretical and empirical reasons to believe function as mediators of the relation between income and both achievement and socioemotional outcomes. According to the cumulative risk perspective, poor children experience more adverse conditions across a range of contexts. The multiplicity of these adverse conditions create an overabundance of difficulties, hardships, and distress that overwhelm their coping abilities, throw their stress-response system into disequilibrium, and set off a cascade of physiological adaptations that put them at increased risk for diminished working memory, achievement and socioemotional functioning (Evans & Kim, 2013). Empirically-identified risk factors in the context of poverty that are likely to be salient contributors to cumulative stress, include: economic strain, poor housing conditions and home disorder, family turmoil, and neighborhood environments that are disadvantaged and dangerous. Here, each of these risks is discussed, in turn.

Low-income families face a multitude of stressors related to *economic strain*: for example, not being able to keep up with the challenges of meeting the family's basic needs, such as providing sufficient food and clothing, and paying rent, utility costs, healthcare expenses, and other bills (Burchinal et al., 2008; Newland, Crnic, Cox, & Mills-Koonce, 2012). But economic strain reflects more than just one's objective income in relation to one's needs: it also reflects one's subjective perceptions that one's current income is inadequate. As such, measures of economic strain may also include anxiety and worry due to high debt levels, employment insecurity, having had to borrow money, having been hassled by a bill collector, lack of healthcare insurance or chronic health problems, or uncertainty about the future (Kalil & Dunifon, 2007; Leininger & Kalil, 2014).

Poverty-related stressors such as material hardship, food insufficiency, inability to pay bills, welfare receipt, parental job loss, have been found to be associated with a higher likelihood of behavior problems and diminished academic functioning in children (Conger, Conger, & Elder, 1997; McDonald, Sigman, Espinosa, & Neumann, 1994; Murphy et al., 1998; Smith, Brooks-Gunn, Kohen, & McCarton, 2001; Strom, 2003). Economic strain can affect children indirectly, through its influence on parental mental health and parenting behaviors (Grant et al., 2000), but it can also affect children directly (Grant et al., 2005; Wadsworth & Santiago, 2008). Children's own subjective experience of stress related to their family's economic hardship and strain can create a high level of cognitive load that inhibits emotional regulation and decision-making abilities (Mani, Mullainathan, Shafir, & Zhao, 2013). Grant and colleagues (2005), for example, found that economic stressors ranging from "my family does not have enough money to pay our bills" to "during the past year, our lights, heat, gas or telephone have been turned off" were directly associated with children's externalizing symptoms, with no significant indirect effects through inconsistent or harsh parenting behavior.

Income can also impact a family's housing choices and thus the *housing conditions*, or physical home environment, in which a child lives. Poor children are much more likely than non-poor children to live in homes with greater structural problems and toxins, lack of heat, inadequate plumbing, overcrowding, less privacy, and more noise (Evans, 2004; Evans & Seagert, 2000; Iceland & Bauman, 2007; Leventhal & Newman, 2010; Vernon-Feagans, Garrett-Peters, DeMarco & Bratsch-Hines, 2012). Moreover, there is a limited but growing research that suggests that substandard physical housing conditions such as the presence of toxins, exposure to noise, crowding, restrictions on outdoor play, housing quality and housing type are associated with greater symptoms of child anxiety, physiological markers of stress, and diminished child cognitive and socioemotional functioning (Dahl, Ceballo, & Huerta, 2010; Evans, Rhee, Forbes, Allen, & Lepore, 2000; Evans & Wener, 2007; Kujala & Brattico, 2009; Schapkin, Falkenstein, Marks, & Griefahn, 2006). Most of these studies incorporated statistical controls for socioeconomic status, indicating that physical home conditions affect these child outcomes over and above the effects of income alone. Like economic strain, the physical condition of the home may be reflective of financial resources, but is also likely an additional source of chaos and stress in the lives of low-income children as well as their parents (Evans, 2006). Indeed, in a longitudinal study Blair and colleagues (2011) found that low-SES children residing in lower quality housing had elevated cortisol over their first four years of life. In addition, unsafe, crowded, and noisy home conditions may limit or disrupt children's exploration, play and interactions with others, which also has ramifications for their cognitive and socioemotional development (Ferguson, Cassells, MacAllister, & Evans, 2013).

The experience of poverty is not only associated with contextual risks with respect to families' physical home environments, but also with the social and *psychological environment in their homes*. There is a considerable amount of research documenting increased family turmoil (e.g., parenting stress and depression, marital conflict, family instability, and exposure to domestic violence) among lower-income families (Bradley & Corwyn, 2002; Conger & Donnellan, 2007; Conger, Schofield, Conger, & Neppl, 2010; Grant et al. , 2003; Margolin & Gordis, 2004; McLanahan, 2009; Vernon-Feagans et al., 2012). Children as young as two have been found to be responsive to the distress among family members (Cummings, Zahn-Waxler, & Radke-Yarrow, 1981), and such intra-family stress, instability, conflict, and violence can impact child's ability to feel safe in their home environments and to regulate their own level of arousal (Dadds & Powell, 1991; Lee, 2001; Margolin & Gordis, 2004). Research has further shown that exposure to family turmoil has been associated with increased behavioral problems, such as aggression (Halpern, 2004), as well as delayed cognitive and language development (Neisser et al., 1996).

As with housing conditions, a family's income can greatly influence the *neighborhood environment* in which a child lives. Compared to children growing up in middle-to-high-income families, poor children are more likely to live in economically depressed neighborhoods, where there is greater incidence of violence and crime, higher levels of pollutants, more deteriorated buildings and other neighborhood problems, fewer safe places to play or engage in physical activity, and less access to healthy food (Briggs-Gowan, Ford, Fraleigh, McCarthy, & Carter, 2010; Cradock et al., 2005; Ellen, Mijanovich, & Dillman, 2001; Israel et al., 2006; Sharkey, 2013). Such neighborhoods are also characterized by greater residential transience, fewer opportunities for social connection and support, and limited access to stable role models (Leventhal & Newman, 2010; Sampson, Morenoff, & Gannon-Rowley, 2002; Sharkey, 2013; Thompson, Flood, & Goodvin, 2006). Moreover, social services and resources such as educational, childcare, and enrichment programs are less accessible in highly disadvantaged neighborhoods, and those that are accessible may be insufficient or poor in quality (Burchinal, Nelson, Carlson, & Brooks-Gunn, 2008; Fuller, Kagan, Caspary, & Gauthier, 2002; Leventhal & Brooks-Gunn, 2000; Sampson, Morenoff, & Gannon-Rowley, 2002; Sharkey, 2013).

Many of these characteristics of disadvantaged neighborhoods have been consistently linked with high levels of stress and poor developmental outcomes. Children living in poor, high-crime neighborhoods report experiencing more stressors than those living in more advantaged neighborhoods (Attar et al., 1994). Exposure to neighborhood stress has been found to be associated with increased levels of a range of internalizing and externalizing symptoms including fear, anxiety, depression, aggression, and post-traumatic stress disorder (Cooley-Quille, Boyd, Frantz, & Walsh, 2001; Dempsey, 2002; Eamon, 2002; Kliewer et al., 1998; Richters & Martinez, 1993; Schwab-Stone et al., 1999). Such factors have also been reported to account for sizable portions of differences with respect to educational outcomes. For example, Ainsworth (2002) found that, controlling for family income, a host of family characteristics, and school effects, living in a neighborhood one standard deviation below the mean was associated with a 3.65 point lower score on standardized achievement tests, when compared to children living in a neighborhood one standard deviation above the mean.

The Evolution of the Concept of Cumulative Risk

The concept of cumulative risk was originally posited in order to take into account the high likelihood, as noted above, of the co-occurrence of multiple risk factors for child development in the context of poverty. It is influenced not only by the bioecological (Bronfenbrenner & Morris, 2006) model of development, but also by the transactional (Sameroff, 1995; Thelan & Smith, 2006) model of development. In addition to highlighting the multiple interrelated contexts in which children are embedded and which influence their development, transactional models (Sameroff, 1995; Thelan & Smith, 2006) underscore the constant interplay and bidirectional influence of the various elements within the whole system. In other words, bidirectional interactions and adaptations are constantly occurring between the individual and his/her contexts and also among the contexts themselves in a way that cannot be predetermined. Together, these models of development provide a framework for understanding the experience of poverty as not simply occurring in isolation nor operating solely at the family level, but rather as related to child developmental outcomes by means of a whole host of associated environmental structural, psychological, and social factors at various levels whose synergistic influence may be greater than that of the factors individually.

Early investigations of the role of cumulative risk on child development focused on the combinatory power of parent and family characteristics that commonly accompany poverty and tend to be highly correlated with child outcomes as well as with each other: for example, lower parental education, occupational status or job prestige, single parenthood, large households, maternal mental health, and marital discord. Using data drawn from the Isle of Wight longitudinal study, Rutter (1979) found that no single risk factor (which in this case also included paternal criminality and child involvement with foster care) was significantly linked to child psychiatric disorder. However, the presence of two risk factors led to a more than fourfold increase in the likelihood of disorder, and the presence of four risk factors led to a tenfold increase, suggesting a multiplicative effect for increased numbers of risk factors.

Sameroff and colleagues (Peck, Sameroff, Ramey, & Ramey, 1999; Sameroff, 2000; Sameroff, Bartko, Baldwin, Baldwin, & Seifer, 1998; Sameroff, Seifer, Baldwin, & Baldwin, 1993; Sameroff, Seifer, Barocas, Zax, & Greenspan, 1987) adapted and extended Rutter's measure of cumulative risk to also include a wider range of risk factors. Their later studies (Peck, Sameroff, Ramey, & Ramey, 1999; Sameroff, 2000; Sameroff, Bartko, Baldwin, Baldwin, & Seifer, 1998), in particular, made a concerted effort to incorporate multiple risk factors from different ecological levels, from family process factors to peer group, school, and community characteristics. Across all of these studies and using several different datasets (though none nationally representative), they found that the more risk factors to which a child was exposed, the greater the likelihood of a range of maladaptive outcomes – both academic and socioemotional – in early childhood all the way through adolescence (Peck et al., 1999; Sameroff et al., 1987;

Sameroff, et al., 1993; Sameroff et al., 1998). In their 1998 analyses, Sameroff and colleagues calculated odds-ratios and reported that the relative risk for a child's academic performance to fall in the bottom quartile increased almost seven times, from 7% for those in the low-risk group (exposed to 3 or fewer risk factors, out of a total of 20) to 45% for those in the high-risk group (exposed to more than 8 risk factors). The odds ratios for falling into the bottom quartile with respect to psychological adjustment and problem behavior was 5.7 and 3.5 respectively.

Similar findings have been reported by other researchers using different samples and different sets of cumulative risk factors, and examining both concurrent and longitudinal child outcomes, suggesting that these results are fairly robust (Deater-Deckard, Dodge, Bates, & Pettit, 1998; Evans & English, 2002; Gutman et al., 2003; Lengua et al. 2007; Rauh et al., 2003). Moreover, follow-up analyses in a number of these studies support the premise underlying the concept of cumulative risk: that it is the number of risks rather than the type of risk that matters in predicting child outcomes. For example, both Deater-Deckard and Sameroff and their respective colleagues (Deater-Deckard et al., 1998; Peck et al., 1999; Sameroff et al., 1987; Sameroff, et al., 1993) found that families who experienced similar numbers of total risks did not necessarily experience the same combination of risks. However, these qualitative differences in risk factors were not significantly related to differences in outcomes among children in same risk category (i.e., low, moderate, or high cumulative risk exposure).

Some studies have noted, however, that when models using cumulative risk indices are compared to multiple regression models that include the same factors entered individually, the latter tend to account for more variance in child outcomes (Burchinal, Roberts, Hooper, & Zeisel, 2000; Deater-Deckard, Dodge, Bates, & Pettit, 1998). Hooper and colleagues (1998) found this to be the case with respect to some outcomes, but reported that the cumulative risk model accounted for more variance in behavioral outcomes. Burchinal and colleagues (2000) also found that the cumulative risk index more successfully predicted developmental change over time. Finally, it is also worth mentioning that most of these studies created cumulative risk indices by first dichotomizing individual risk factors measures such that families received a score of 1 if they met or exceed the risk threshold on that particular indicator and a score of 0 if they fell below, and then adding them all up. More recently, Burchinal and colleagues (2008) have suggested that averaging across individual risk factor measures not only uses all of the information in each risk variable, reflecting the level as well as the presence of a risk factor – but is also a stronger predictor of child outcomes than when simply calculated as a count of risk factors.

Despite some lingering questions, two fundamental ideas emerged from these studies of cumulative risk. The first is that while many of these risk factors associated with poverty are highly correlated, not all of these risk factors are present in each individual case. Sameroff, Gutman, and Peck (2003) draws a useful comparison with health-related risk factors: "Hypertension, obesity, lack of exercise, and smoking all made significant contributions to heart disease at the population level, but for any single affected individual there was a different combination of these factors" (p. 365). Similarly with respect to the development of cognitive and socioemotional competence in children, it is likely not a specific single factor but the presence of various factors that causes poor outcomes. Second, these risk factors act synergistically. Families facing poverty are more likely to experience other life stressors that may exacerbate the strains of poverty and negatively impact their children's development. Thus, the cumulative impact of multiple individual risk factors will be greater than the individual risk factors themselves.

The Importance of Examining Change

While much of the work on cumulative risk has been groundbreaking, the study of this topic is in early stages, with many open questions of scientific and practical significance. Questions concerning the extent to which change matters are cases in point. Does cumulative risk exposure lessen for families that rise out of poverty, for example? And, in turn, does child well-being and functioning improve if risk exposure is reduced? The answers to such questions are precursors to answering critical questions of whether policies or interventions designed to ameliorate a child's exposure to cumulative risk will give rise to improved outcomes. Moreover, understanding when, how, and for whom changes in family income most strongly predict changes in cumulative risk exposure, and in turn changes in child outcomes can provide critical guidance in designing interventions and policy around the specific developmental periods, areas of risk, and/or protective factors that are most likely to induce the greatest positive impact on children's lives.

The study of change is also useful for purposes of cause probing. Among non-experimental designs, the study of change can offer the advantage of controlling for unobserved between-child and between-family heterogeneity, which may be a serious source of bias in many correlational developmental studies (Duncan, Magnuson, & Ludwig, 2004; Foster, 2010; McCartney, Bub, & Burchinal, 2006). Specifically, within-child estimators of associations between changes in predictors and outcomes (i.e., fixed-effects estimators) offer control for unobserved between-child heterogeneity. While these methods are not a panacea for selection effects or a substitute for randomized studies of change (i.e., time-varying sources of "omitted variable bias" are a concern and reasonable amounts of change in the phenomena of interest are required), they are a recommended tool for probing causal hypotheses with non-experimental data with the benefit of adding ecological validity to the study of phenomena that are not stable over time (Allison, 2009).

However, research that examines change with respect to a child's exposure to multiple poverty-associated risk factors is sparse. Nonetheless, a 20-year longitudinal study by Sroufe, Egeland, Carlson, and Collins (2005) does suggest that changes in a child's circumstances at later developmental time points can improve early developmental trajectories. Using data from the Minnesota Study of Risk and Adaptation From Birth to Adulthood, they found that diminished parental life stress or depression, or an increase in social support, was associated with improvements in child socioemotional and behavioral functioning.

While not specifically looking at changes in a child's exposure to stressful contexts, other researchers examined variation in a family economic conditions and similarly found that increases in income-to-needs were associated with improvements in a range of child outcomes. Using longitudinal data from the NICHD Study of Early Childcare, Hackman, Gallops, Evans, and Farah (2015) found that decreases in income-to-needs, across a time period spanning 54 months to Grade 5, were significantly associated with decreases in a child's planning efficiency and approached significance in their association with decreases in a child's working memory across that same time period. Dearing and colleagues (2006), also using the NICHD data, found not only that positive changes in income-to-needs were associated with diminished externalizing behavior from 54 months through Grade 1, but also that the benefits of changes in family income were significantly greater for children who were chronically poor compared to those who were never poor. In a previous study (Dearing, McCartney, & Taylor, 2001), they also found that when children from poor families experienced relatively large changes in income-to-needs (> 1 SD above the mean change for poor families) during a child's early years, those children demonstrated outcomes at 36 months similar to their nonpoor peers with respect to school readiness, receptive and expressive language, and positive social behaviors. Dearing and colleagues' work, in particular, highlights not only the important information that change models can provide but also the necessity of examining potential moderators.

To date, very little, if any, research has examined whether changes in income might lead to changes in exposure to contextual risk factors, and whether these changes in risk exposure are related to changes in children's cognitive, academic, and socioemotional functioning. Even if income and exposure to multiple contextual risks are highly correlated, differences in income may not always translate into differences in economic strain, housing conditions, neighborhood quality, or intra-family conflict. For example, economic strain may remain stable despite increases in income, perhaps due to decreases in welfare-related benefits, such as health insurance, as income rises beyond a threshold level (Kalil & Duniform, 2007). Similarly, neighborhood quality may remain stable despite increases in income, because it may take fairly large increases in income to allow for a change of residence and/or a family may choose for a variety of reasons to remain in their same home. More research is needed to better understand whether and how changes in income might lead to changes in exposure to multiple contextual risks and whether changes in risk exposure is, in turn, associated with changes in child outcomes.

Potential Moderators of Interest

The effects of exposure to stressful circumstances can be confounded by a variety of factors, including individual differences in the level and timing of poverty and its associated risks/stressors, as well as the presence, or lack thereof, of protective factors. Understanding the role of these moderating factors is also critical for gaining an accurate picture of how exposure to such circumstances affects child development, as well as for designing effective interventions.

Level and timing of poverty and its associated contextual risks. The relationship between income and child outcomes is generally not linear, with smaller differences in income having a larger effect on child outcomes for families at the lower end of the income distribution. Moreover, families at this lower end of the income distribution have fewer resources – social and psychological, as well as material – that could help them climb out of poverty, and thus they are also more likely to experience persistent poverty, which has been found to be more deleterious to child development than temporary or episodic poverty (Brooks-Gunn & Duncan, 1997; Linver et al., 2002; Magnuson & Duncan, 2006; Wagmiller, Lennon, Kuang, Alberti, & Aber, 2006). However, there is also evidence that suggests that lower-income families experience less stability, or greater volatility, in income – due to, for example, job loss, divorce, or other negative life events (Corcoran & Chaudry, 1997; Magnuson & Votruba-Drzal, 2009). These greater fluctuations can also be associated with larger negative effects with respect to child outcomes (Dearing, McCartney, & Taylor, 2001; Dearing, McCartney, & Taylor, 2006; Dearing & Taylor, 2007). Thus it is important to consider families' level of income when examining how income influences child development.

In addition, the effects of family income may depend crucially on developmental timing. Duncan and colleagues have found, across numerous studies, that the association between family income and both child cognitive and noncognitive skills are stronger when poverty is experienced in early childhood compared to (or in some cases, controlling for) middle childhood or early adolescence (Brooks-Gunn & Duncan, 1997; Duncan & Brooks-Gunn, 1997; Duncan & Brooks-Gunn, 2000; Duncan, Kalil, & Ziol-Guest, 2010; Duncan & Magnuson, 2013). Similar patterns have been reported by the small number of experimental and quasi-experimental studies that have examined associations between family income and child outcomes; these studies found higher levels of early academic achievement and school attendance for children who were elementary-aged or younger at the time of the intervention but not for those who were adolescents at the time of the intervention (Morris et al., 2006; Salkind & Haskins, 1982). This research is in line with evidence from neuroscience that early childhood years could also be an especially critical time period because that is when a child's brain is developing in leaps and bounds, which may make young children more sensitive to environmental influences (Sapolsky, 2004; Shonkoff & Phillips, 2000). And it is further supported by Chunha and Heckman's (2007, 2008) work, which shows that more than half of the inequality in adult lifetime earnings is due to factors determined before age 18, and the income gaps in cognitive and noncognitive skills seen at age 18 are themselves, in large part, already present at age five. That is, large disparities in both the academic and socioemotional skills of children due to income inequalities are already present prior to school entry, persist through the school years, and ultimately lead to income inequalities in adulthood.

Additionally, there is research that suggests that changes in cumulative risk, or at least some indicators of risk, may also matter more when children are younger. In their re-analysis of the Moving to Opportunity data, Chetty, Hendren, and Katz (2015) discovered that children who moved to low-poverty neighborhoods when they were young enjoyed much greater economic success than similarly aged children who were not part of the experimental group, while children who moved when they were older experience no gains or perhaps worse outcomes, possibly the result of the potentially greater disruptive effects of moves in the adolescent years, paired with fewer benefits of such a move, given the shorter amount of time spend in a better neighborhood. In a second study, Chetty and Hendren (2015) used earning records to track the moves and later outcomes of five million people over 17 years; and when comparing families who made the similar moves but at different points in their child's lives, they found that the earlier a family moved to a good neighborhood, the better the children's long-run outcomes. Given that both of these studies highlighted stronger effects of changes in risk for younger children specifically among initially high-risk families, it is also worth exploring whether initial level of risk plays a role in moderating the associations between changes in risk and children's outcomes.

Race/ethnicity. Finally, recent research suggests that race may play a role in the degree to which differences in income are related to certain indicators of contextual risk. Chetty and Hendren (2015) also found that African-American and Hispanic children are much more likely to live in neighborhoods with lower median incomes (relative to their own family incomes) than White and Asian children with similar family incomes. For example, in Milwaukee and Newark, where Black and White children of similar family incomes grew up in the most economically different neighborhoods, on average, an African-American child with a family income of $50,000 lives in a neighborhood with a median income 1.8 times smaller than an average White family with the same income. Reardon, Fox, and Townsend (2015) also found large and persistent racial differences in neighborhood contexts even among households with the same annual income. This suggests certain risk factors – particularly those related to neighborhood and housing conditions – may be less responsive to changes in income for African-American or Hispanic families than White or Asian families.

Furthermore, considerable research indicates that prejudice and discrimination can exacerbate stress. Non-White Americans are disproportionately more likely experience major forms of prejudice and discrimination, such as being unfairly stopped, search, questioned or threatened by police; neighbors making life difficult for them or their family after moving into a new neighborhood; a teacher or advisor discouraging them from continuing their education; or experiencing unfair treatment when receiving healthcare (American Psychological Association, 2016). A range of research across multiple fields has found that such perceptions of discrimination and even the anticipation of prejudice can result in exacerbated physiological and psychological stress responses (Adam et al., 2015; Chiao & Blizinsky, 2013; Hicken, Lee, Morenoff, House, & Williams, 2014; Sawyer, Major, Casad, Townsend, & Mendes, 2012). Hicken and colleagues (2014) further note that the hypervigilance that these stress responses trigger may represent an important and unique source of chronic stress.

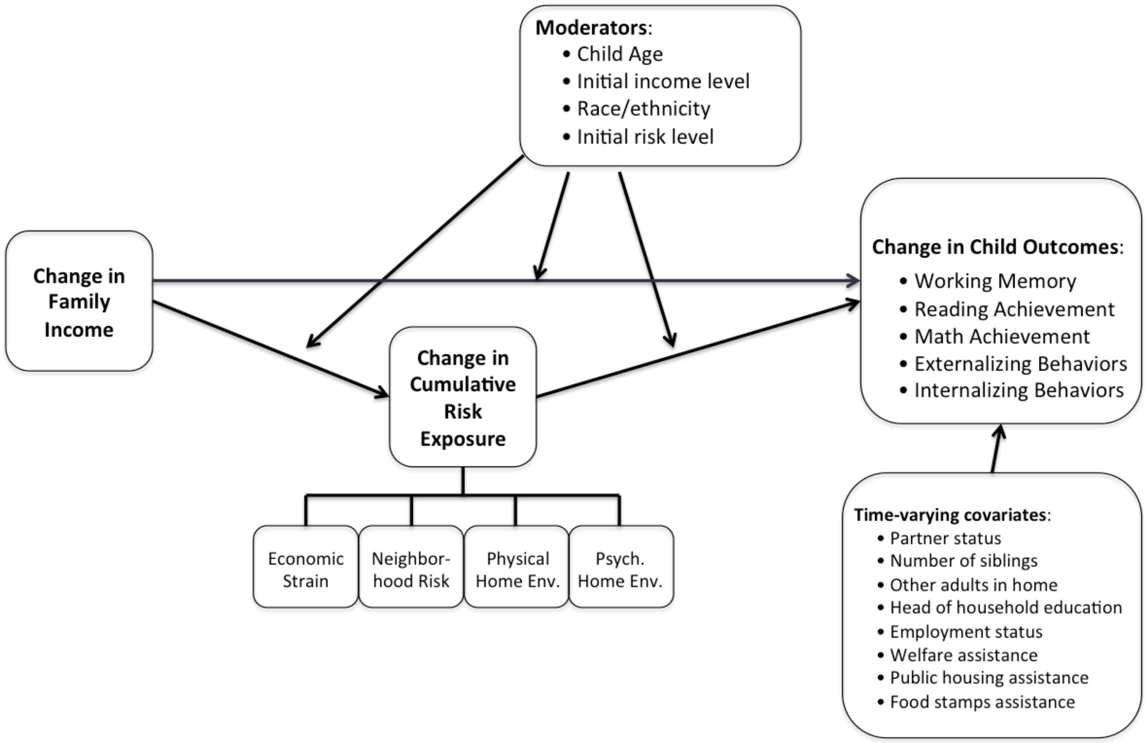
However, the very limited research on the moderating role of race/ethnicity on the association between income and cumulative risk/stress *or* on the association between cumulative risk/stress and child developmental outcomes is conflicting. Some studies (for example, Mistry, 2010) found no difference in the strength of these relationships by race/ethnicity. Other studies (e.g., Raver, Gershoff, & Aber, 2007) have noted stronger associations between income and food insecurity for Black and Hispanic families compared to White families, as well as between parenting stress and marital conflict and child outcomes. Further research is needed to explore these potential differences.

The Present Study

The primary aim of the present study was to examine within-child associations between family income, cumulative risk exposure, and a range of child outcomes: working memory, math and reading achievement, and externalizing and internalizing behaviors. Toward this aim, I first investigated (1) whether changes in family income are associated with changes in children's working memory, math and reading achievement, and externalizing and internalizing behaviors. Next, I investigated (2) whether changes in family income predict changes in children's cumulative exposure to contextual risks in their homes and communities, and in turn (3) whether changes in cumulative risk exposure predict changes in child working memory, math and reading achievement, and externalizing and internalizing behaviors. In so doing, I examined (4) whether changes in cumulative risk exposure mediates associations between changes in family income and changes in child cognitive skills, math and reading achievement, and socioemotional outcomes.

In addition, a secondary aim of this study was to investigate (5) moderators that may exacerbate or ameliorate harmful consequences of economic disadvantage and risk exposure. Of particular interest is whether the magnitude of associations between income, cumulative risk, and child outcomes are moderated by: (a) the initial income level of a family, (b) timing of family income changes and its associated risks with respect to a child's development or age, and (c) the initial cumulative risk level of a family. In addition, in light of research indicating that prejudice and discrimination heighten stress, and exacerbate its harms (American Psychological Association, 2016), I will explore (d) race/ethnicity as a potential moderator of the associations between income and cumulative risk exposure and of the associations between cumulative risk exposure and child outcomes. The figure below presents the conceptual model underlying the present study, and it is followed by specific research hypotheses.

Figure 1. Conceptual Model



With respect to the primary set of research questions addressed by the present study, it is hypothesized that (1) changes in income will be positively associated with changes in children's working memory and academic achievement, and negatively associated with changes in children's externalizing and internalizing behaviors. Moreover, it is hypothesized that (2) gains in income will predict reductions in cumulative risk, and that (3) reductions in cumulative risk will in turn predict improved child outcomes. It is further hypothesized that (4) associations between changes in family income and child academic and socioemotional functioning will be mediated by changes in cumulative risk.

With regard to moderators, given previous evidence suggesting that the relations between income (and its associated risk) and child outcomes vary by income and/or risk level (Dearing, McCartney, & Taylor, 2001), it is hypothesized that changes in income and risk exposure will be most strongly associated with one another and with the child outcomes for low-income and high-risk families. Further, based on findings that early childhood could be an especially critical time period in which children are more sensitive to environmental influences than at older ages (Brooks-Gunn & Duncan, 1997; Duncan & Brooks-Gunn, 1997; Duncan & Brooks-Gunn, 2000; Duncan, Kalil, & Ziol-Guest, 2010; Duncan & Magnuson, 2013; Sapolsky, 2004; Shonkoff & Phillips, 2000), it is hypothesized that the magnitude of the relations between changes in income and changes in risk exposure and changes in child outcomes will be stronger when children are younger.

Finally, in the context of evidence that African-Americans and Hispanics are disproportionately exposed to contextual risks such as poor housing conditions and neighborhood crime in comparison to Whites, regardless of their family income (Reardon, Fox, & Townsend, 2015), it is hypothesized that associations between changes in income and changes in risk may be smaller for minority populations. However, in light of research suggesting that discrimination and prejudice can exacerbate stress (Adam et al., 2015; Chiao & Blizinsky, 2013; Hicken, Lee, Morenoff, House, & Williams, 2014; Sawyer, Major, Casad, Townsend, & Mendes, 2012), it is hypothesized that associations between changes in risk and changes in child outcomes will be stronger for non-White than White participants.

CHAPTER 3: METHODS

Sampling

The data for the present research were drawn from the Panel Study of Income Dynamics (PSID) and its Child Development Supplement (CDS). The PSID began as a nationally representative longitudinal study with approximately 5,000 families in 1968. Beginning in 1997, more extensive information on children ages 0-12 in a sub-sample of families ($N = 3{,}500$) was collected through the Child Development Supplement (CDS). Through caregiver interviews, questionnaires, home observations, and direct assessment, information was gathered about children's academic and socioemotional functioning, home life, and childcare experiences, as well as a variety of caregiver characteristics such as verbal comprehension ability, mental health, parenting values, and more. Follow-up assessments were conducted 5 and 10 years later, in 2002 and 2007.

Because the present study was designed to compare equivalent measures with respect to the same children from early childhood through their school years, the current sample was limited to children who were 3-7 years old at the time of the first CDS interview in 1997 ($N = 1{,}384$). These children were 5-12 years old at the time of the 2002 interview ($N = 1{,}146$) and 13-17 years old at the time of the 2007 interview ($N = 998$). Within this analytic sample, there were missing data on individual measures, as well as missing data due to attrition over the waves. Missing data were imputed using multiple imputation by chained equations, implemented in Stata 13.1 (Royston, 2004, 2005). After imputation, sampling weights, which adjust for potentially biasing selection factors, differential response, and attrition, were incorporated in all analyses. The use of these weights make the sample representative of children in the US aged 3-7 years in 1997.

Finally, because the CDS dataset contains a number of sibling pairs, sibling effects were controlled for by clustering within families.

Just over half of the analytic sample (53%) were male. Approximately 45% of the sample were Caucasian/White, 41% were African-American, 8% were Latino American, and 6% represented other ethnicities. As a whole, families were representative of a wide range of socioeconomic conditions, with 22% of the sample having a family income at Wave 1 below the federal poverty level, 22% having an initial family income between 100% and 200% of the federal poverty level, and 56% having an initial family income greater than 200% of the federal poverty level.

Measures

Family income. Total pretax income of all family members living in the household was measured annually in the PSID by means of parent report. The PSID definition of family, used in this analysis, included single-person families and unmarried cohabiting couples who share resources, as well as families related by blood, marriage or adoption. Because the PSID bottom-coded family income at $1 prior to 1994, all waves were bottom-coded for consistency.

Income data collected at each time point in the PSID represents the total pretax income of all family members living in the household averaged during the year *prior* to each CDS data collection time point. In other words, for the first wave of data, which was collected in 1997, family income measures reflect the household's total pretax 1996 income. To ease interpretation of coefficients in the statistical models, income values were divided by 10,000; thus, a one-unit change corresponded to a $10,000 change in family income. In addition, in light of past evidence of nonlinear income effects, residual plots were examined, which suggested that associations were nonlinear. Thus, a log transformation of the family income measure was used; in the statistical models, a 1-unit change in income, therefore, corresponded to the estimated effect of a $10,000 change in family income for families at the lowest end of the income distribution. Estimates for families at higher levels of income were calculated as x/y for which x is the estimated income coefficient and y is the family income level (divided by 10,000).[1]

Cumulative risk exposure. Following a conventional approach to quantifying cumulative risk (Evans, Brooks-Gunn, & Klebanov, 2011), while at the same time taking into account conceptual and empirical distinctions that emerged in a principal component factor analysis of these data (see Appendix A), a child's exposure to cumulative poverty-associated contextual risk factors was measured by means of a composite index that was created at each of the three data collection time points across four domains of risk: economic strain, neighborhood risk factors, physical home environment, and psychological home environment.

Each distinct context of risk was itself composed of multiple indicators. Economic strain, for example, included 15 parent-report items based on yes/no responses to a single question asked of the primary householder, namely "Have you done any of the following or have any of the following happened as a result of economic problems?" Drawn from Conger and Elder's (1994) work measuring experiences of economic or financial stress

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[1] As is typical following multiple imputation, there were a small number of negative income values. Following best practice recommendations, these values were not bottom-coded (Enders, 2010). However, prior to log transformations this required that a constant of 20 be added to all values, and for presentation purposes coefficients needed to be divided by 20 to ensure that they represented the effect of $10,000 income change for positive income values at the low end of the distribution rather than that effect at implausible negative levels of income.

and practical responses to such financial pressures, items included: fallen behind in paying bills, borrowed money from friends or relatives, applied for government assistance, and had your wages garnished by a creditor. Neighborhood risk factors included two parent-report Likert-scale items: the extent to which the neighborhood is a good place to raise children and how safe it is to walk around alone in the neighborhood after dark. Both of these items were drawn from measures used in the National Longitudinal Survey of Youth (NLSY, 1979). Physical home environment was based on four direct-observation items from the Home Observation for Measurement of the Environment (HOME; Bradley, 1994) subscale: whether or not the home was structurally unsafe or toxins were present (yes/no) and whether the physical environment was monotonous, was cluttered, or was unclean (Likert-scale). Finally, psychological home environment was composed of three parent-report-based scales/items: maternal depression (based on the 6-item nonspecific psychological distress scale developed by Kessler et al., 2002); aggravation in parenting or parenting stress (drawn from a 7-item scale developed by ChildTrends, 1993, to measure parenting stress that may result from changes in employment, income and other factors); and intra-family conflict/violence (drawn from items developed for the National Survey of Families and Households by Sweet, Bumpass, & Call, 1988). All items were recoded, as needed, such that higher/positive values represented greater risk.

Following the conventional approach to creating cumulative risk indices (see, e.g., Burchinal, Roberts, Hooper, & Zeisel, 2000; Deater-Deckard, Dodge, Bates, & Pettit, 1998), all items were dichotomized such that families received a score of 1 if they met or exceed the risk threshold on that particular item and a score of 0 if they fell below. For example, if a head of household responded to the question, “How safe is it to walk around alone in your neighborhood after dark?” by saying it was “somewhat dangerous” or “extremely dangerous,” the child’s level of risk for this item would have been coded as high, or present (i.e., coded as 1), whereas if the head of household responded that it was “fairly safe” or “completely safe,” the threshold measure for this indicator would be low or not present (i.e., coded as 0). For continuous items/scales (e.g., economic strain, maternal depression, parenting stress), the threshold level of risk was set at 1 standard deviation above the mean at Wave 1. Dichotomized items were averaged within each risk domain to create a composite measure within each distinct context of risk (economic strain, neighborhood risk, physical home disorder, and psychological home environment risk). Each of these composite measures (which themselves had a range from 0 to 1, such that each risk domain contributed equally to the index) was then averaged to create the total cumulative risk exposure index at each data collection time point.

Child working memory. Child outcomes covered three broad domains related to children’s educational success. Working memory is one of three components of executive functioning and is thought to be regulated by the prefrontal cortex and is an aspect of cognitive functioning that has been found to be negatively associated with poverty and cumulative stress (see, e.g., Arnsten, 2009; Farah et al., 2006; Raver, Blair, & Willoughby, 2013). In the present study, working memory was measured by means of the Wechsler backwards digit span test (Wechsler, 1974), during which a child is asked listen to a sequence of numbers and repeat them back in reverse order, with the length of each sequences of numbers increasing as the child responds correctly. In this way, the backward digit span test measures a child’s ability to manipulate relevant information in one's mind while holding it in memory. The Wechler Digit Span tests have been found to have good validity and a high internal reliability in the range of .70-.90 (Conway et al., 2005).

Child achievement. Achievement was assessed using the Woodcock-Johnson Achievement Test Revised (WJR; Woodcock & Johnson, 1989) Applied Problems and Letter-Word subscales. The Applied Problems subtest measures a student's ability to analyze and solve math problems, while the Letter-Word subtest assesses a student's word identification skills and is often used as a measure of reading ability. The WJR is a comprehensive assessment of children's cognitive skills and achievement that has been shown to have good reliability and validity (McGrew, Werder, & Woodcock, 1991). The split-half reliability for the Applied Problems test is .93 (Schrank, McGrew, & Woodcock, 2001). W-scores on each of these subtests allow for comparison of changes in scores across different time points and measurement of growth from the preschool years through late adulthood on a single common scale.

Child socioemotional functioning. Socioemotional functioning was assessed by means of the externalizing and internalizing subscales of the Behavior Problem Index. The Behavior Problem Index included 28 parent-response questions about specific behaviors their children exhibited over the previous three months. Thirteen items in the overall index refer to internalizing problems, which are characterized by an overcontrol of emotions (e.g., social withdrawal, feelings of worthlessness), while 16 items refer to externalizing problems, which are characterized by an undercontrol of emotion (e.g., displays of irritability, rule breaking). The Behavior Problem Index also has been shown to have good validity and reliability, ranging from .89-.90 (Zill, 1990).

Time. Data collection wave was used as a time-varying predictor variable in place of time, with 0 representing the initial status, or first data collection time point in 1997, 5 representing the second data collection time point in 2002, and 10 representing the third data collection time point in 2007. In this way the passage of time is represented in single year increments.

Covariates and moderator variables. In addition, a range of covariates, including child, mother, and family characteristics that could be confounded with child outcomes, was used in the proposed study. Time-varying family characteristics included partner status, number of siblings living in the home, whether or not there are additional adults living in the home, the head of household's education level, and indicator variables indicating employment status, and whether the family received welfare/TANF, public housing, or food stamps assistance (e.g. coded as 0 for no and 1 for yes). Several time-invariant variables, such as family income and child age at Wave 1, and child race/ethnicity were also investigated as moderators of the associations between income, cumulative risk, and child outcomes. The time-invariant variable, Child Age at Wave 1, was used, rather than treating child age as a time-varying variable, in order to account for the differing ages of the children at the start of the study. A complete list of measures is also provided in Appendix B.

Analytic Technique

Fixed effects models that use longitudinal data with common measures within individuals across development are one of the best non-experimental methods for addressing questions concerning whether change matters: in this case, whether changes in family income and changes in exposure to cumulative risk matter for children's developmental outcomes. Moreover, among non-experimental designs, change models provide better support for causal argument than models that do not account for change, because modeling change controls for unobserved influences associated with both the outcome and the predictor (Dearing, McCartney, & Taylor, 2001; Dearing, McCartney, & Taylor, 2006; Dearing & Taylor, 2007); there could still be bias associated with time-varying factors, but overall, "omitted variable bias" is thought to be greatly reduced in fixed effects models.

Fixed effects models were estimated – using Stata 13.1 (StataCorp, 2013) – in the present study to examine within-child associations between family income, cumulative risk exposure, and child outcomes. Specifically, within-child, fixed effects of time-varying predictors (including time-varying covariates, as well as family income and cumulative risk) and interactions between multiple time-varying predictors were estimated in a Level-1 model to examine the average within-person associations between these predictors and the time-varying outcomes (i.e., child working memory, math and reading achievement, and externalizing and internalizing behaviors). Consider, for example, Equation 1 (corresponding to Research Question 2), in which cumulative risk exposure (*Y*) is expressed as a function of time-varying family income and time-varying covariates (number of siblings, partner status of head of household, whether or not there are additional adults living in the home, head of household education level, employment status, and whether family received any government assistance in the form of welfare/TANFF, public housing, or food stamps).

Equation 1:

$$
\begin{aligned}
(Y_{it} - \overline{Y_{i\bullet}}) = {} & \beta_{10}(Inc_{it} - \overline{Inc_{i\bullet}}) + \beta_{20}(Sibs_{it} - \overline{Sibs_{i\bullet}}) \\
& + \beta_{30}(Partner_{it} - \overline{Partner_{i\bullet}}) + \beta_{40}(OthAdlts_{it} - \overline{OthAdlts_{i\bullet}}) \\
& + \beta_{50}(ParentEd_{it} - \overline{ParentEd_{i\bullet}}) + \beta_{60}(Employed_{it} - \overline{Employed_{i\bullet}}) \\
& + \beta_{70}(Welfare_{it} - \overline{Welfare_{i\bullet}}) \\
& + \beta_{80}(PubHousing_{it} - \overline{PubHousing_{i\bullet}}) \\
& + \beta_{90}(FoodStamps_{it} - \overline{Foodstamps_{i\bullet}}) + \beta_{100}(Wave_{it} - \overline{Wave_{i\bullet}}) \\
& + u_{it}
\end{aligned}
$$

In the model, is the estimated within-child association between family income and cumulative risk exposure. Similar models were estimated with respect to investigating the associations between changes in family income and changes in children's working memory, math and reading achievement, and externalizing and internalizing behaviors (Research Question 1), as well as between changes in cumulative risk and each of these child outcomes (Research Question 3).

In addition, in Equation 2, an example of a model examining time-varying interactions between cumulative risk and child age at Wave 1 is provided.

Equation 2:

$$
\begin{aligned}
(Y_{it} - \overline{Y_{i\bullet}}) = {} & \beta_{11,0}(CR_{it} - \overline{CR_{i\bullet}}) + \beta_{11,1}Age_{i\bullet}X(CR_{it} - \overline{CR_{i\bullet}}) + \beta_{10}(Inc_{it} - \overline{Inc_{i\bullet}}) + \\
& \beta_{20}(Sibs_{it} - \overline{Sibs_{i\bullet}})| + \beta_{30}(Partner_{it} - \overline{Partner_{i\bullet}}) + \\
& \beta_{40}(OthAdlts_{it} - \overline{OthAdlts_{i\bullet}}) + \beta_{50}(ParentEd_{it} - \overline{ParentEd_{i\bullet}}) + \\
& \beta_{60}(Employed_{it} - \overline{Employed_{i\bullet}}) + \beta_{70}(Welfare_{it} - \overline{Welfare_{i\bullet}}) + \\
& \beta_{80}(PubHousing_{it} - \overline{PubHousing_{i\bullet}}) + \beta_{90}(FoodStamps_{it} - \\
& \overline{Foodstamps_{i\bullet}}) + \beta_{10,0}(Wave_{it} - \overline{Wave_{i\bullet}}) + u_{it}
\end{aligned}
$$

In this and similar equations, a term was included for estimating the cross-level interaction between a time-invariant moderator (e.g., child age at Wave 1) and a time-varying predictor (e.g., cumulative risk exposure). As with all time-invariant variables in fixed-effects equations, the main effect of the time-invariant moderator drops out.

Missing Data

Missing data was imputed using multiple imputation by chained equations, implemented in Stata 13.1 to create 20 complete datasets (Royston, 2004, 2005). After imputation, sampling weights, which adjust for potentially biasing selection factors, differential response, and attrition, were incorporated in all analyses. Sibling effects were controlled for by clustering within families.

CHAPTER 4: RESULTS

Results are presented as follows. First, descriptive statistics and preliminary analyses are provided. Then, results related to each of the research questions being investigated is addressed in turn: namely, (1) are changes in family income associated with changes in child outcomes, (2) are changes in family income associated with changes in cumulative risk exposure, (3) are changes in cumulative risk exposure associated with changes in child outcomes, and (4) do changes in cumulative risk mediate the with-child associations between family income and child outcomes. After estimates are reported for the sample as a whole, results are presented for analyses examining (5) whether each of the above associations are moderated by, (a) initial family income level, (b) child age, and (c) race/ethnicity. An additional moderator of within-child associations between cumulative risk and child outcomes was also examined: namely, (d) initial level of cumulative risk.

Descriptive Statistics and Preliminary Analyses

Table 1 presents descriptive statistics for time-invariant and time-varying child and family characteristics. Children in the sample ranged from 3 to 7.99 years of age at Wave 1, with an average age of 5.45 years. Just over half of the sample children were male (52%). Forty-five percent of the sample children were White, 41% were African-American, 8% were Hispanic, and 6% represented other ethnicities.

Trends in family income and cumulative risk exposure. Looking at the primary predictor of interest, inflation-adjusted family income increased, on average, by about 36% from Wave 1 to Wave 3. The percentage of the sample with a family income below the federal poverty level decreased from 22% at Wave 1 to 14% at Wave 3 (a decrease of

38%), and fairly proportional decreases were seen in the percentages of the sample that were living in public housing (-37%) or receiving food stamps (-31%). The percentage of the sample that received TANF, however, declined much more dramatically from 11% at Wave 1 to under 3% at Wave 3 (a 77% decrease). The vast majority of this decline occurred between Wave 1 and Wave 2 (-68%), coinciding with the welfare reform enacted toward the end of 1996 (the year to which Wave 1 income data corresponds).

The primary mediator of interest, average cumulative risk exposure, increased for the sample by approximately 25% from Wave 1 to Wave 2, but then decreased 27% to slightly below its Wave 1 level at Wave 3. A similar pattern was seen for average economic strain (+11% between Wave 1 and Wave 2; -15% between Wave 2 and Wave 3) and neighborhood risk levels (+14% between Wave 1 and Wave 2; -19% between Wave 2 and Wave 3). Physical home disorder increased fairly steadily by about 20% each wave, while psychological home risk increased about 36% between Wave 1 and Wave 2 and then another 5% between Wave 2 and Wave 3.

Table 1. Descriptive Statistics for Time-Invariant and Time-Varying Child and Family Characteristics

Variable	**Wave 1** (Early Childhood) n = 1,384[a]	**Wave 2** (Middle Childhood) n = 1,141[b]	**Wave 3** (Adolescence) n = 994[b]	Range (Across waves)
Time-invariant				
Child age at Wave 1	5.45 (1.40)			3-7.99
Male (%)	52.6%			
White (%)	45.2%			
African American (%)	41.2%			
Hispanic (%)	7.7%			
Other ethnicity (%)	6.0%			
Child birth weight	7.22 (1.42)			1.25-11.56
Maternal verbal ability	30			4-43
Time-varying				
Family income (in 1996 dollars)[c]	43,170 (42,891)	55,105 (61,037)	58,718 (62,386)	1-955,626
Head is partnered (%)	66.2%	62.4%	54.0%	
Number of siblings in HH	1.25 (1.08)	1.41 (1.08)	1.30 (1.10)	0-9
Other adults live in HH (%)	14.0%	12.2%	12.9%	
Head education (years)	12.57 (2.52)	12.79 (2.42)	12.90 (2.41)	1-17
Head is employed (%)	82.6%	87.1%	83.4%	
Received TANF (%)[c]	11.4%	3.7%	2.6%	
Living in public housing (%)	12.1%	9.8%	7.6%	
Received food stamps (%)[c]	24.5%	15.5%	16.8%	
Below federal poverty level (%)[c]	22.3%	14.7%	13.8%	
Cumulative Risk Index	0.12 (0.18)	0.15 (0.19)	0.11 (0.18)	0-1
Economic strain	0.18 (0.38)	0.20 (0.40)	0.17 (0.37)	0-1
Neighborhood risk	0.14 (0.28)	0.16 (0.31)	0.13 (0.28)	0-1
Physical home disorder	0.09 (0.22)	0.11 (0.21)	0.13 (0.23)	0-1
Psychological home risk	0.14 (0.23)	0.19 (0.28)	0.20 (0.29)	0-1
Working memory	1.44 (1.72)	4.98 (2.02)	5.67 (2.14)	0-14
Reading achievement	396.74 (44.78)	501.80 (24.95)	523.54 (22.37)	539-589
Math achievement	436.24 (34.70)	503.50 (19.12)	524.23 (19.56)	514-590
Externalizing behaviors	5.90 (3.79)	5.88 (4.27)	5.07 (4.23)	0-17
Internalizing behaviors	2.06 (2.36)	3.31 (3.22)	2.75 (3.22)	0-14

[a] The total number of children included in models. [b] Sample sizes at each assessment time indicate the number of children with nonmissing outcome data at that assessment. At each assessment time, descriptive statistics for time-varying variables are reported only for those children with nonmissing outcome data. [c] Family income, TANF, food stamps, and poverty status correspond to the year prior to data collection.

Data assumptions. Prior to running inferential analyses, all study variables were examined for normality, and relations between continuous predictors/mediators and outcome variables were checked for linearity. Given previous evidence of non-linearity of associations between income and outcomes, a log transformation of income was created and compared to the non-log-transformed measure of family income. The total variance explained (R-square) was larger for the log transformation model, indicating that the transformation seemed to help the model fit. Moreover, log transformed coefficients were larger than those using income levels, further evidence that the effect of income was larger at the low end of the distribution than at the center of the distribution or above. All other variables were deemed to be acceptable for analysis without transformations.

Bivariate associations. Table 2 presents bivariate correlations for the primary variables of interest at each Wave. Correlations show consistent significant negative associations between family income and cumulative risk at all time points, positive associations between family income and cognitive/academic outcomes, and negative associations between income and externalizing. Cumulative risk show negative associations with child cognitive/academic outcomes at concurrent and later, but not necessarily prior, waves. Correlations also indicated moderate stability in income, risk, and outcomes over time.

Table 2. Intercorrelations between Family Income, Cumulative Risk, and Child Outcomes at Each Wave

	Inc1	Inc2	Inc3	Risk1	Risk2	Risk3	WM1	WM2	WM3	Reading1	Reading2	Reading3	Math1	Math2	Math3	Ext1	Ext2	Ext3	Int1	Int2	Int3
Income1																					
Income2	0.62***																				
Income3	0.66***	0.69***																			
Risk1	-0.28***	-0.22***	-0.24***																		
Risk2	-0.19***	-0.23***	-0.24***	0.33***																	
Risk3	-0.09***	-0.09***	-0.13***	0.29***	0.45***																
WM1	0.17***	0.18***	0.22***	-0.12***	-0.01	0.06+															
WM2	0.21***	0.17***	0.19***	-0.12***	-0.15***	-0.05	0.33***														
WM3	0.21***	0.14***	0.20***	-0.18***	-0.14***	-0.10**	0.25***	0.49***													
Reading1	0.17***	0.19***	0.22***	-0.12***	-0.02	0.09**	0.76***	0.32***	0.21***												
Reading2	0.29***	0.25***	0.28***	-0.19***	-0.23***	-0.02	0.43***	0.49***	0.40***	0.54***											
Reading3	0.31***	0.26***	0.30***	-0.24***	-0.22***	-0.11***	0.34***	0.42***	0.46***	0.38***	0.81***										
Math1	0.19***	0.20***	0.21***	-0.15***	-0.04	0.07*	0.70***	0.32***	0.24***	0.82***	0.50***	0.36***									
Math2	0.34***	0.29***	0.33***	-0.23***	-0.25***	-0.02	0.52***	0.47***	0.40***	0.55***	0.70***	0.64***	0.53***								
Math3	0.34***	0.29***	0.34***	-0.23***	-0.19***	-0.12***	0.33***	0.43***	0.44***	0.29***	0.57***	0.64***	0.34***	0.73***							
Ext1	-0.11***	-0.07*	-0.11***	0.20***	0.11***	0.03	-0.14***	-0.11***	-0.07*	-0.16***	-0.17***	-0.12***	-0.14***	-0.21***	-0.15***						
Ext2	-0.16***	-0.11***	-0.13***	0.25***	0.37***	0.14***	-0.09**	-0.14***	-0.09*	-0.08*	-0.19***	-0.19***	-0.09**	-0.19***	-0.16***	0.48***					
Ext3	-0.20**	-0.06*	-0.09**	0.20***	0.21***	0.15***	-0.12**	-0.16***	-0.15***	-0.13***	-0.22***	-0.22***	-0.13***	-0.22***	-0.25***	0.42***	0.61***				
Int1	-0.10***	-0.02	-0.06*	0.18***	0.13***	0.06*	0.04	-0.03	-0.07*	0.09**	-0.03	-0.05	0.04	-0.07*	-0.10**	0.57***	0.30***	0.26***			
Int2	-0.10**	-0.04	-0.08**	0.21***	0.32***	0.15***	-0.06+	-0.14***	-0.07*	-0.09**	-0.17***	-0.15***	-0.07*	-0.17***	-0.14***	0.37***	0.69***	0.47***	0.38***		
Int3	-0.05	-0.02	-0.06+	0.17***	0.17***	0.13***	-0.05	-0.16***	-0.20**	-0.05	-0.15***	-0.15***	-0.07*	-0.16***	-0.19***	0.31***	0.45***	0.70***	0.36***	0.57***	

*** p < .001; ** p < .01; * p < .05; + p < .10

Unconditional models. Unconditional mean models were estimated to examine the proportion of variance in each of the outcomes that was due to between-child differences versus within-child differences (i.e., change over time), and unconditional growth models were estimated to provide a baseline for quantifying the proportion of the outcome variation explained by subsequent models. Results from both the unconditional means models and the unconditional growth models are presented in Table 3. These models suggest that there is considerable within-child variation, above and beyond that explained by the passage of time/natural development, worth exploring through fixed effects modeling.

Table 3. Unconditional Models for Child Cognitive, Achievement, and Socioemotional Outcomes

	Working Memory	**Reading**	**Math**	**Externalizing**	**Internalizing**
Unconditional Means Model					
Intercept	4.22 (0.05)***	476.74 (0.38)***	490.52 (0.34)***	5.88 (0.10)***	2.87 (0.08)***
Within-Child Variance ($sigma_e^2$)	9.77	5420.96	2606.41	11.04	7.21
Unconditional Growth Model					
Intercept (Initial Status)	2.03 (0.08)***	412.33 (0.93)***	445.36 (0.80)***	6.06 (0.12)***	2.42 (0.09)***
Slope (Rate of Change/Yr)	0.44 (0.02)***	12.88 (0.19)***	9.03 (0.15)***	-0.04 (0.03)	0.09 (0.02)***
Remaining Unexplained Within-Child Residual Variance ($sigma_e^2$)	4.94	1272.35	576.17	11.00	7.00
% of Within-Child Variation in Outcome Associated with Linear Time	49%	77%	78%	0%	3%

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Within-Child Associations between Family Income and Child Outcomes

In order to address my first research question – namely, whether changes in family income were related to changes in children's outcomes – fixed effects regression models were used to estimate within-child associations between family income and each of the following outcomes: child working memory, reading and math achievement, and externalizing and internalizing behaviors. Coefficients and standard errors for family income and time-varying covariates (number of siblings, partner status of head of household, whether or not other adults were living in the home, head education, head employment status, and whether or not the family received TANF or food stamps, or were living in public housing) from models assessing the main effects of income are presented in Table 4. For the sample as a whole, prior to considering the moderators of interest, changes in family income were not *directly* associated with changes in any of the child outcomes examined.

Table 4. Regression Coefficients from Fixed Effects Models Examining Associations between Changes in Income and Changes in Child Cognitive, Achievement, and Socioemotional Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Log of Income	0.02 (0.03)	0.36 (0.52)	0.13 (0.29)	0.01 (.03)	0.01 (0.03)
# of Siblings	0.48 (0.09)***	12.63 (1.67)***	7.06 (1.19)***	0.40 (0.14)**	0.42 (0.12)**
Partner Status	0.02 (0.20)	-0.36 (3.47)	-1.95 (2.38)	-0.14 (0.30)	-0.28 (0.24)
Other Adults in Home	-0.01 (0.09)	-2.79 (1.73)	-0.47 (1.25)	0.00 (0.13)	-0.25 (0.14)+
Parent Ed	0.06 (0.07)	1.90 (1.24)	1.43 (0.91)	-0.01 (0.09)	-0.08 (0.07)
Employed	0.37 (0.22)+	5.56 (3.48)	3.27 (2.70)	0.36 (0.41)	0.63 (0.30)*
Welfare	0.72 (0.32)*	2.46 (5.91)	0.36 (4.13)	0.12 (0.44)	0.38 (0.34)
Public Housing	0.05 (0.28)	-0.99 (4.81)	-2.68 (3.68)	-0.44 (0.49)	-0.20 (0.33)
Food Stamps	-0.42 (0.20)*	-10.33 (3.15)**	-5.58 (2.49)*	-0.80 (0.34)*	-0.40 (0.29)
Wave/Time (in years)	0.36 (0.01)***	13.50 (0.20)***	9.37 (0.15)***	-0.09 (0.02)***	0.10 (0.02)***
Intercept	-1.26 (2.18)	340.94 (34.53)	406.92 (21.30)***	4.98 (2.40)*	2.03 (1.96)

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Within-Child Associations between Family Income and Cumulative Risk Exposure

In order to address my second research question and as a first step toward examining whether changes in family income had *indirect* effects on children's outcomes through cumulative risk, within-child associations between family income and cumulative risk were estimated. Coefficients and standard errors for family income and time-varying covariates (number of siblings, partner status of head of household, whether or not other adults were living in the home, head education, head employment status, and whether or not the family received TANF or food stamps, or were living in public housing) are presented in Table 5. Results indicated that changes in family income were significantly associated with changes in cumulative risk. For families at the lower end of the income spectrum, a $10,000 increase in income was associated with a 0.16-unit decrease in cumulative risk, which is a decrease of 89% of a standard deviation. Because a log transformation of income was used, a $10,000 change in income was associated with smaller changes in cumulative risk for families at the mean or above on income (i.e., $52,600).

Within-child effects of income were also estimated for each of the individual risk domain indicators in order to examine the relative responsivity of each of these risk domains to changes in income. These results are also presented in Table 5. Changes in income were significantly associated with changes in economic strain and physical home disorder, but not neighborhood risk or psychological home environment. For families at the lower end of the income spectrum, a $10,000 change in income was associated with a 0.26-unit decrease, or about two-thirds of a standard deviation decrease, in economic strain. The same change in income was associated with a 0.16-unit decrease in physical home disorder, which is about three-quarters of a standard deviation in physical home disorder.

Table 5. Regression Coefficients from Fixed Effects Models Examining Associations between Changes in Income and Changes in Cumulative Risk Exposure and Individual Risk Indicators

Time-Varying Variables	Cumulative Risk	Economic Strain	Neighborhood Risk	Physical Home Disorder	Psychological Home Environment
Log of Income	-0.16 (0.05)**	-0.26 (0.06)***	-0.08 (0.07)	-0.16 (0.08)*	-0.17 (0.13)
# of Siblings	0.05 (0.01)***	0.00 (0.02)	0.04 (0.02)	0.01 (0.01)	0.10 (0.02)***
Partner Status	-0.06 (0.02)**	-0.03 (0.04)	-0.04 (0.03)	-0.01 (0.03)	-0.12 (0.06)*
Other Adults in Home	0.01 (0.01)	-0.01 (0.02)	0.03 (0.02)	-0.04 (0.02)+	0.03 (0.03)
Parent Ed	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)	-0.01 (0.02)
Employed	0.00 (0.03)	-0.02 (0.04)	-0.01 0.03)	0.02 (0.03)	0.02 (0.06)
Welfare	-0.07 (0.04)+	-0.09 (0.07)	-0.03 (0.06)	-0.08 (0.06)	-0.04 (0.09)
Public Housing	0.00 (0.03)	-0.11 (0.06)+	0.09 (0.04)*	0.00 (0.05)	-0.04 (0.07)
Food Stamps	0.06 (0.02)*	0.01 (0.05)	0.08 (0.05)+	0.07 (0.04)*	0.03 (0.05)
Wave/Time (in years)	0.02 (0.00)***	0.00 (0.00)*	0.02 (0.00)***	0.00 (0.00)	0.04 (0.00)***
Intercept	0.50 (0.18)**	0.86 (0.24)***	0.32 (0.25)	0.56 (0.26)	0.75 (0.48)

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Within-Child Associations between Cumulative Risk and Child Outcomes

In order to address my third research question – whether changes in cumulative risk were associated with changes in child outcomes – within-child associations between cumulative risk and each of the following child outcomes were estimated: child working memory, reading and math achievement, and externalizing and internalizing behaviors. Coefficients and standard errors for cumulative risk and time-varying covariates (including log of family income in addition to covariates from previous models: number of siblings, partner status of head of household, whether or not other adults were living in the home, head education, head employment status, and whether or not the family received TANF or food stamps, or were living in public housing) are presented in Table 6. Changes in cumulative risk were significantly associated with changes in children's reading and math scores, and externalizing behaviors. A 1-unit decrease in cumulative risk (the equivalent of moving from high-risk to normal or below risk on all of the domains included in the cumulative risk index) was associated with a 10.92-point increase in reading scores, a 6.92-point increase in math scores, and a 1.24-point decrease in externalizing behaviors. A 0.25-unit decrease in cumulative risk (the equivalent of moving from high-risk to normal or below average risk in just one of the four domains included in the cumulative risk index, which is a more practical metric for presenting effect sizes for cumulative risk and will be used moving forward) is associated with a 2.73-point increase in reading scores (approximately 9% of a standard deviation), a 1.73-point increase in math scores (approximately 7% of a standard deviation), and 0.31-point decrease in externalizing behaviors (approximately 8% of a standard deviation).

Table 6. Regression Coefficients from Fixed Effects Models Examining Associations between Changes in Cumulative Risk and Changes in Child Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Cumulative Risk	-0.15 (0.24)	-10.92 (4.24)**	-6.92 (2.85)*	1.24 (0.41)**	0.41 (0.37)
Log of Income	0.02 (0.03)	0.28 (0.52)	0.07 (0.29)	0.02 (0.03)	0.01 (0.03)
# of Siblings	0.49 (0.09)***	13.16 (1.73)***	7.40 (1.21)***	0.34 (0.14)*	0.34 (0.14)*
Partner Status	0.01 (0.20)	-1.03 (3.48)	-2.37 (2.39)	-0.07 (0.31)	-0.07 (0.31)
Other Adults in Home	-0.00 (0.09)	-2.70 (1.74)	-0.41 (1.26)	-0.01 (0.13)	-0.01 (0.13)
Parent Ed	0.06 (0.07)	1.98 (1.24)	1.49 (0.92)	-0.02 (0.10)	-0.02 (0.10)
Employed	0.37 (0.22)+	5.61 (2.39)	3.30 (2.69)	0.36 (0.41)	0.36 (0.41)
Welfare	0.71 (0.32)*	1.73 (5.90)	-0.10 (4.11)	0.20 (0.42)	0.20 (0.42)
Public Housing	0.05 (0.28)	-1.00 (4.76)	-2.69 (3.63)	-0.44 (0.48)	-0.44 (0.48)
Food Stamps	-0.41 (20)*	-9.72 (3.18)**	-5.19 (2.47)*	-0.86 (0.35)*	-0.86 (0.35)*
Wave/Time (in years)	0.47 (0.01)***	13.72 (0.24)***	9.51 (0.17)***	-0.12 (0.02)***	-0.12 (0.02)***
Intercept	-1.18 (2.17)*	346.44 (34.67)***	410.42 (21.50)***	4.36 (2.39)+	4.36 (2.39)+

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Mediation Analyses

In order to address my fourth research question – whether changes in cumulative risk exposure mediates associations between changes in family income and changes in child cognitive skills, math and reading achievement, and socioemotional outcomes – direct and indirect effects of income through cumulative risk, were calculated for child working memory, reading and math achievement, and externalizing and internalizing behaviors. Coefficients and standard errors for income effects with and without cumulative risk in the model are presented in Table 7. Results indicate small but significant indirect effects of changes in income through changes in cumulative risk on reading, math, and externalizing scores.

Table 7. Direct and Indirect (through Cumulative Risk Exposure) Effects of Changes in Income on Child Outcomes

	Income Only + Controls	Cumulative Risk Exposure Added	
	Direct Effect of Income	*Direct Effect of Income*	*Indirect Effect of Income*
Working Memory	0.02 (0.03)	0.02 (0.03)	0.00 (0.00)
Reading	0.36 (0.52)	0.28 (0.52)	0.09 (0.04)*
Math	0.13 (0.29)	0.07 (0.29)	0.06 (0.03)*
Externalizing	0.01 (0.03)	0.02 (0.03)	-0.01 (0.00)*
Internalizing	0.01 (0.03)	0.01 (0.03)	0.00 (0.00)

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Variations in Associations by Initial Income Levels

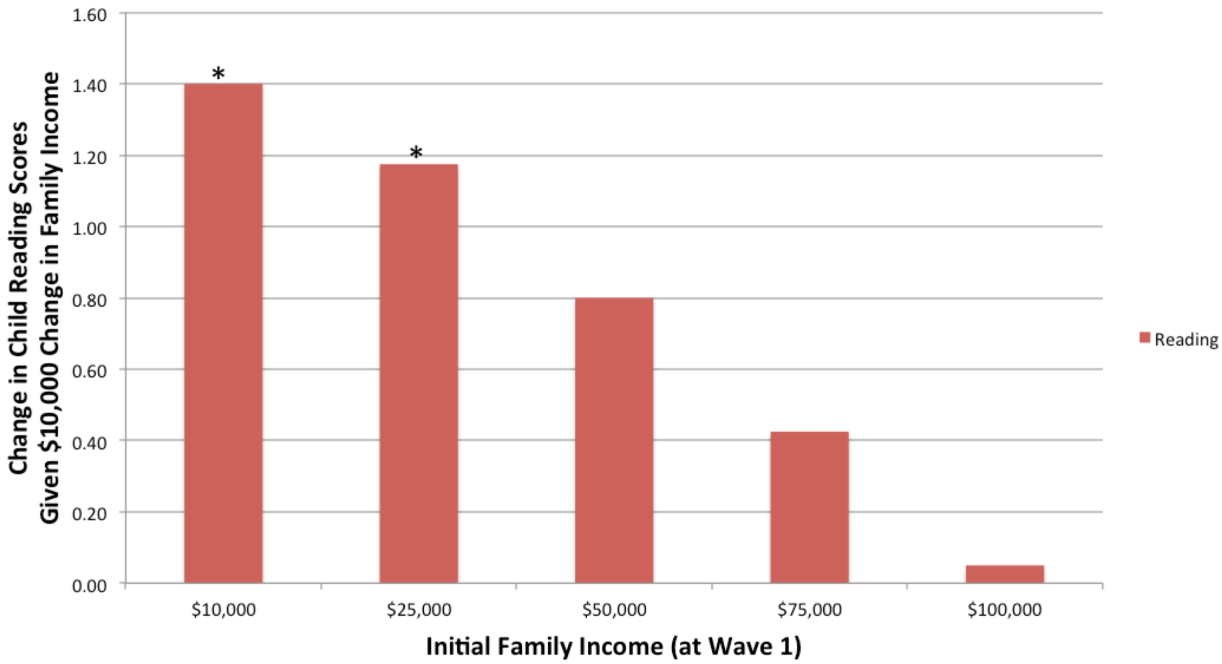
A second set of models considered whether within-child associations between income, cumulative risk, and child outcomes varied for families at different points on the income spectrum at Wave 1, addressing the question of whether changes in income and/or cumulative risk mattered more for families who started out with less. First, the interaction between changes in family income and income level at Wave 1 was included in models examining within-child associations between family income and child outcomes. Coefficients and standard deviations for this set of models are presented in Table 8. Results indicated that associations between changes in family income and child working memory and reading achievement varied significantly by initial income level. Changes in family income mattered more for children from families with lower initial income levels with respect to working memory and reading achievement. Increases in income significantly predicted increases in working memory and reading scores for children in families with initial incomes less than or equal to $25,000 (approximately 200% of the 1997 federal poverty level). For families making $10,000 a year, a $10,000 increase in income was associated with a 0.08-point (4% of a standard deviation) increase in working memory and a 1.40-point increase (5% of a standard deviation) in reading achievement. Figure 2 depicts how the within-child associations between income and reading scores decreases as a family's initial income (at Wave 1) increases for those at the lower end of the income distribution.

Table 8. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Income Level at Wave 1 on Child Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Log of Income	0.08 (0.04)*	1.55 (0.73)*	0.44 (0.44)	-0.03 (0.05)	0.02 (0.04)
# of Siblings	0.47 (0.09)***	12.68 (1.61)***	7.02 (1.19)***	0.40 (0.14)***	0.42 (0.12)**
Partner Status	-0.02 (0.20)	-0.65 (3.30)	-2.13 (2.37)	-0.12 (0.30)	-0.29 (0.24)
Other Adults in Home	-0.02 (0.09)	-3.35 (1.64)*	-0.53 (1.26)	0.01 (0.13)	-0.25 (0.14)+
Parent Ed	0.06 (0.07)	2.39 (1.10)*	1.42 (0.91)	-0.00 (0.09)	-0.08 (0.07)
Employed	0.34 (0.22)	3.41 (3.28)	3.14 (2.72)	0.38 (0.41)	0.62 (0.30)*
Welfare	0.72 (0.32)*	1.38 (5.90)	0.38 (4.14)	0.11 (0.43)	0.38 (0.34)
Public Housing	0.05 (0.28)	0.15 (4.73)	-2.68 (3.70)	-0.44 (0.49)	-0.20 (0.34)
Food Stamps	-0.38 (0.20)+	-9.30 (2.95)**	-5.38 (2.49)*	-0.82 (0.34)*	-0.40 (0.29)
Wave/Time (in years)	0.46 (0.01)***	13.47 (0.20)***	9.35 (0.15)***	-0.09 (0.02)	0.10 (0.02)***
Intercept	-2.43 (2.29)	309.88 (35.41)***	400.83 (23.30)***	5.65 (2.53)*	1.91 (2.11)
Income X Income at Wave 1	-0.01 (0.00)*	-0.15 (0.06)**	-0.04 (0.06)	0.00 (0.00)	-0.00 (0.00)

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 2. Associations between Income and Reading Scores by Initial Family Income at Wave 1



Note. Income estimates are for families at the lower end of the income distribution. Because a log transformation of income was used, a $10,000 change in income was associated with smaller changes in scores for families at the mean or above on income (i.e., $52,600).
* $p < .05$

Next, the interaction between changes in family income and initial income (at Wave 1) was included in models examining within-child associations between family income and cumulative risk. Results are displayed in Table 9. The association between changes in family income and cumulative risk did significantly vary by where on the income spectrum a family started out. Changes in family income predicted greater changes in cumulative risk for families whose income was lower at Wave 1. For families whose income at Wave 1 was $10,000, a $10,000 increase in income was associated with a 1.05-point decrease in risk, the equivalent of more than 5 times a standard deviation. As families' initial income increased, the negative association between changes in income and changes in risk over time decreased. This interaction between changes in income and initial income level (or any other interactions) was not seen for any of the individual risk indicators, so results presented here are only for cumulative risk.

Table 9. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Income at Wave 1 on Cumulative Risk Exposure

Time-Varying Variables	**Cumulative Risk**
Log of Income	-1.44 (0.57)*
# of Siblings	0.05 (0.01)***
Partner Status	-0.06 (0.02)*
Other Adults in Home	0.01 (0.01)
Parent Ed	0.01 (0.01)
Employed	0.01 (0.02)
Welfare	-0.07 (0.04)+
Public Housing	0.00 (0.03)
Food Stamps	0.06 (0.02)*
Wave/Time (in years)	0.02 (0.00)***
Intercept	0.60 (0.18)**
Income X Income at Wave 1	0.39 (0.17)*

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Finally, the interaction between cumulative risk exposure and income level at Wave 1 was included in models examining within-child associations between cumulative risk and child outcomes. Coefficients and standard deviations for this set of models are presented in Table 10. Results indicated that associations between cumulative risk and children's externalizing and internalizing behaviors, but not cognitive/academic outcomes, varied significantly by initial income level. Changes in cumulative risk had stronger associations with externalizing and internalizing behaviors for children in families with lower initial income levels, with decreases in cumulative risk predicting larger decreases in externalizing and internalizing behaviors. For children in families at the lowest end of the income spectrum at Wave 1, a 0.25-unit decrease in cumulative risk was associated with a 0.49-point decrease in externalizing behaviors (.13 SD) and a 0.24-point decrease in internalizing behaviors (.10 SD). For families with initial incomes of

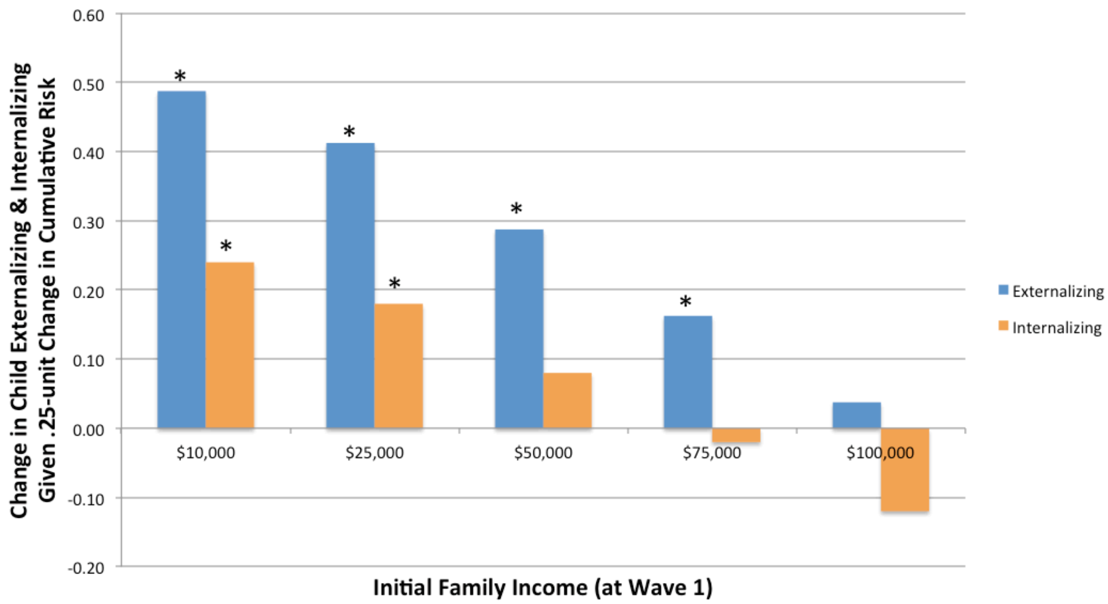
$50,000, a 0.25-unit decrease in cumulative risk was associated with a 0.29-point decrease in externalizing behaviors (0.08 SD) and decreases in cumulative risk were not associated with decreases in internalizing behaviors. Figure 3 depicts how the associations between cumulative risk exposure and externalizing and internalizing behaviors vary by a family's initial income level.

Table 10. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Cumulative Risk and Income Level at Wave 1

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Cumulative Risk	0.13 (0.37)	-5.52 (6.62)	-4.96 (4.60)	2.15 (0.67)**	1.12 (0.54)*
Log of Income	0.02 (0.03)	0.27 (0.51)	0.07 (0.29)	0.02 (0.03)	0.01 (0.03)
# of Siblings	0.49 (0.09)***	13.20 (1.72)***	7.42 (1.21)***	0.34 (0.13)*	0.40 (0.12)**
Partner Status	0.01 (0.20)	-1.04 (3.48)	-2.387 (2.39)	-0.07 (0.31)	-0.26 (0.24)
Other Adults in Home	-0.00 (0.09)	-2.64 (1.74)	-0.39(1.26)	0.00 (0.13)	-0.24 (0.14)+
Parent Ed	0.06 (0.07)	1.96 (1.25)	1.48 (0.92)	-0.02 (0.10)	-0.08 (0.07)
Employed	0.36 (0.22)	5.51 (3.46)	3.27 (2.69)	0.34 (0.40)	0.61 (0.30)*
Welfare	0.73 (0.32)*	2.50 (6.01)	0.09 (4.16)	0.29 (0.42)	0.49 (0.34)
Public Housing	0.05 (0.29)	-0.93 (4.76)	-2.66 (3.63)	-0.43 (0.47)	-0.19 (0.32)
Food Stamps	-0.42 (0.20)+	-9.78 (3.18)**	-5.21 (2.47)*	-0.88 (0.35)*	-0.43 (0.29)
Wave/Time (in years)	0.47 (0.01)***	13.73 (0.24)***	9.51 (0.17)***	-0.11 (0.02)***	0.09 (0.02)***
Intercept	-1.15 (2.17)	346.98 (34.55)***	410.61 (21.48)***	4.45 (2.39)+	1.90 (1.96)
Cumulative Risk X Income at Wave 1	-0.06 (0.06)	-1.19 (0.82)	-0.43 (0.67)	-0.20 (0.12)*	-0.16 (0.08)*

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 3. Associations between Cumulative Risk and Externalizing and Internalizing Behaviors by Initial Family Income



* *p* < .05

In addition, I investigated whether changes in cumulative risk mediated the moderated effects of changes in income reported above. To demonstrate mediated moderation, two criteria must be met: (1) there must be an overall moderation effect; (2) the moderated indirect effects, via the mediator, must be significant. To establish the second criteria, two separate models were estimated: the moderated effects of income on cumulative risk, and the moderated effects of cumulative risk on each outcome (with the moderated effects of income on the outcomes also included in the model). For mediated moderation to occur, either (2a) the effect of income on cumulative risk depends on the moderator *and* average partial effect of cumulative risk on the outcome is nonzero, and/or (2b) the partial effect of cumulative risk on the outcome depends on the moderator *and* the average effect of income on cumulative risk is nonzero. As a result, the residual moderated effects of income should be reduced in magnitude.

The moderated effects of income by initial income level were evaluated based on the criteria presented above. Analyses indicated that cumulative risk exposure did not mediate the moderated effects of income. In other words, the varied effects between changes in income and child working memory and reading skills by initial income level were not explained by differences with respect to changes in cumulative risk by initial income level. Coefficients and standard errors for moderated income effects with and without the respective interaction term for cumulative risk in the model are presented in Table 11. The residual, direct, moderated effect of income when cumulative risk is in the model is only minimally, if at all, reduced in value when compared to the direct, moderated effect of income when cumulative risk is not included in the model.

Table 11. Direct and Indirect (through Cumulative Risk Exposure) Moderated Effects of Income by Income at Wave 1 on Child Outcomes

	Income Only + Controls	Cumulative Risk Exposure Added	
	Direct Income X Initial Income	*Indirect Income X Initial Income*	*Cumulative Risk X Initial Income*
Working Memory	-0.01 (0.00)*	-0.01 (0.00)*	0.00 (0.02)
Reading	-0.15 (0.06)**	-0.14 (0.06)*	0.01 (0.32)
Math	-0.04 (0.06)	n/a	n/a
Externalizing	0.00 (0.00)	n/a	n/a
Internalizing	-0.00 (0.00)	n/a	n/a

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Variations in Associations by Child Age at Wave 1

In a third set of models, the interaction of family income and child age at Wave 1 was included in order to examine whether the estimated within-child associations between income, cumulative risk, and child outcomes varied for the different "age cohorts" of children – that is, children of different ages at the start of the study. Parallel to the previous set of models, the interaction term between family income and child age at Wave 1 was first entered into the models examining within-child associations between family income and child outcomes. Results for this set of models are presented in Table 12. The associations between income and child cognitive/academic outcomes varied significantly by child age at Wave 1.

Specifically, the associations between family income and child cognitive/academic outcomes were stronger for younger children in the sample, with increases in income significantly predicting increases in working memory, reading and math skills for children under the age of 5 years. For 3-year-olds at the lowest end of the income spectrum, a $10,000 increase in family income was associated with a 4.71-point increase in reading scores, a 4.43-point increase in math scores, and a 0.16-point increase in working memory scores. This roughly corresponds to 15% of a standard deviation (or more than a third of an average year's growth) in reading, 18% of a standard deviation (a half an average year's growth) in math scores, and 8% of a standard deviation (also more than a third of an average year's growth) in working memory scores. For 4-year-olds, this same increase was associated with a reduced, but still significant, increase in cognitive/academic scores.

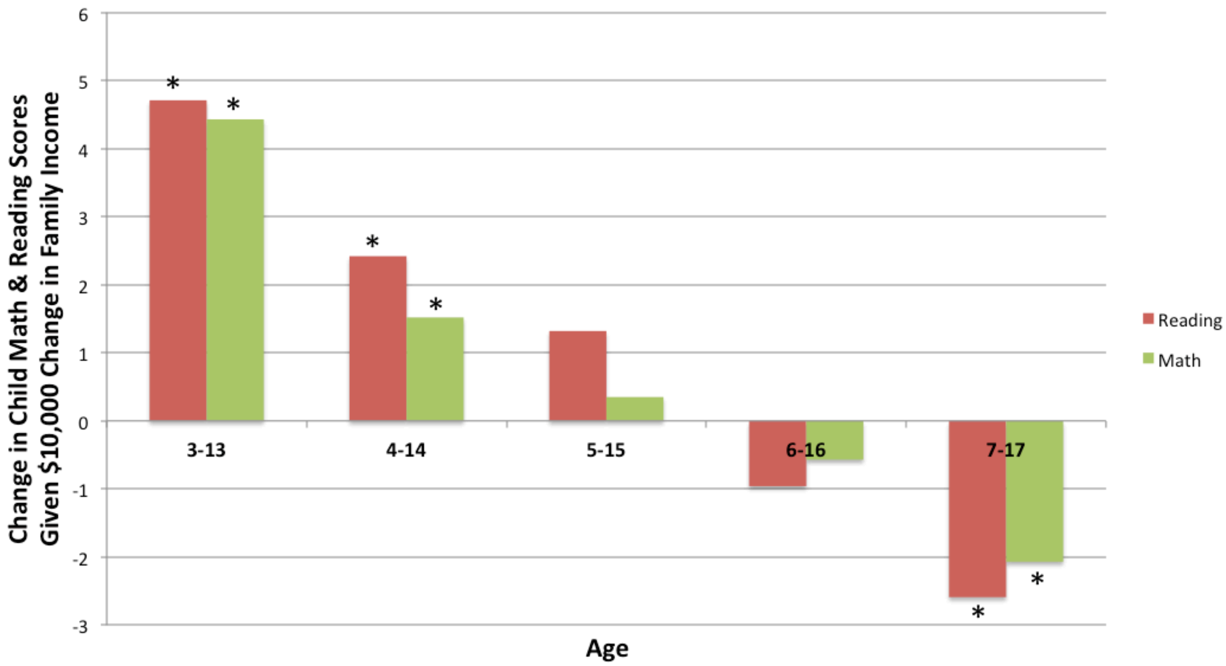
For 5- and 6-year-olds, however, the association between changes in income and changes in scores was essentially 0, and non-significant; and for 7-year-olds, increases in income were associated with diminished scores. In all cases, because a log transformation of income was used, a $10,000 change in income was associated with smaller changes in scores for families at the mean or above on income (i.e., $52,600). Figure 4 depicts how the associations between income and math and reading scores decreases as child age increases for those at the lower end of the income distribution. Due to log transformation of income, the associations between income and math and reading scores are smaller for families at the higher end of the income distribution.

Table 12. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Child Age at Wave 1 on Child Outcomes

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Log of Income	0.16 (0.08)*	4.71 (1.56)**	4.43 (1.29)***	-0.20 (0.12)	0.02 (0.09)
# of Siblings	0.46 (0.09)***	11.92 (1.65)***	6.54 (1.16)***	0.41 (0.14)**	0.42 (0.12)**
Partner Status	0.04 (0.20)	0.19 (3.41)	-1.54 (2.33)	-0.16 (0.30)	-0.28 (0.24)
Other Adults in Home	0.00 (0.09)	-2.55 (1.77)	-0.29 (1.27)	-0.01 (0.13)	-0.25 (0.14)+
Parent Ed	0.06 (0.07)	1.87 (1.23)	1.41 (0.91)	-0.01 (0.09)	-0.08 (0.07)
Employed	0.36 (0.22)+	5.46 (3.44)	3.20 (2.66)	0.36 (0.41)	0.63 (0.30)*
Welfare	0.71 (0.31)	2.13 (5.78)	0.12 (4.02)	0.13 (0.43)	0.38 (0.34)
Public Housing	0.07 (0.29)	-0.12 (4.84)	-2.04 (3.73)	-0.46 (0.49)	-0.20 (0.34)
Food Stamps	-0.42 (0.20)*	-10.28 (3.08)**	-5.54 (2.41)*	-0.80 (0.34)*	-0.40 (0.29)
Wave/Time (in years)	0.46 (0.01)***	13.47 (0.20)***	9.35 (0.14)***	-0.09 (0.02)***	0.10 (0.02)***
Intercept	-2.28 (2.22)	304.62 (33.06)	380.08 (22.90)***	5.83 (2.46)*	1.98 (1.96)
Income X Age Four	-0.07 (0.10)	-2.18 (1.69)	-2.97 (1.36)*	0.20 (0.14)	-0.03 (0.10)
Income X Age Five	-0.11 (0.10)	-3.41 (1.76)+	-4.42 (1.35)**	0.17 (0.14)	0.00 (0.10)
Income X Age Six	-0.19 (0.09)*	-5.70 (1.74)**	-4.92 (1.33)***	-0.26 (0.14)+	-0.01 (0.10)
Income X Age Seven	-0.20 (0.10)*	-7.37 (1.87)***	-6.51 (1.42)***	-0.25 (0.15)+	0.00 (0.10)
Income Estimate at Age 4	0.05 (0.06)	2.43 (0.77)**	1.52 (0.45)***		
Income Estimate at Age 5	0.07 (0.05)	1.32 (0.87)	0.35 (0.49)		
Income Estimate at Age 6	-0.03 (0.04)	-0.96 (0.84)	-0.57 (0.38)		
Income Estimate at Age 7	0.06 (0.04)	-2.59 (1.08)*	-2.07 (0.60)***		

Note. Children Age 3 are the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 4. Associations between Income and Reading and Math Scores by Child Age at Wave 1



Note. Income estimates are for families at the lower end of the income distribution. Because a log transformation of income was used, a $10,000 change in income was associated with smaller changes in scores for families at the mean or above on income (i.e., $52,600).
* $p < .05$

Next, the interaction between changes in family income and child age at Wave 1 was included in a model examining within-child associations between family income and cumulative risk. Results are presented in Table 13. The association between family income and cumulative risk did not vary by child age, indicating that changes in income were related to changes in cumulative risk for all ages fairly equally.

Table 13. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Child Age at Wave 1 on Cumulative Risk

Time-Varying Variables	Cumulative Risk
Log of Income	-0.01 (0.01)
# of Siblings	0.05 (0.01)***
Partner Status	-0.06 (0.02)**
Other Adults in Home	0.01 (0.01)
Parent Ed	0.01 (0.01)
Employed	0.01 (0.02)
Welfare	-0.07 (0.04)+
Public Housing	0.00 (0.03)
Food Stamps	0.06 (0.02)*
Wave/Time (in years)	0.02 (0.00)***
Intercept	0.50 (0.18)**
Income X Age Four	0.00 (0.01)
Income X Age Five	0.00 (0.01)
Income X Age Six	0.00 (0.01)
Income X Age Seven	-0.01 (0.01)

Note. Children Age 3 are the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Finally, the interaction between cumulative risk exposure and child age was included in order to models examining whether the estimated within-child associations between cumulative risk and child outcomes varied by child age. Coefficients and standard deviations for these models are presented in Table 14. Results indicated that associations between cumulative risk and child cognitive and academic outcomes varied significantly by child age at Wave 1, with stronger negative associations seen for older children. For the oldest age groups in the sample (5-, 6- and 7-year-olds), decreases in risk were associated with improved working memory and reading and math scores. For 7-year-olds in the sample, for instance, a 0.25-unit decrease in cumulative risk was associated with a 0.23-point increase (.12 SD and half an average year's growth) in working memory, a 11.01-point increase (.35 SD, or almost an average year's growth) in reading achievement, and a 6.36-point increase (.26 SD, or more than two-third's an average year's growth) in math achievement. As the age of children decreases, however, the effects of cumulative risk diminish, becoming non-significant for 3- and 4-year-olds.

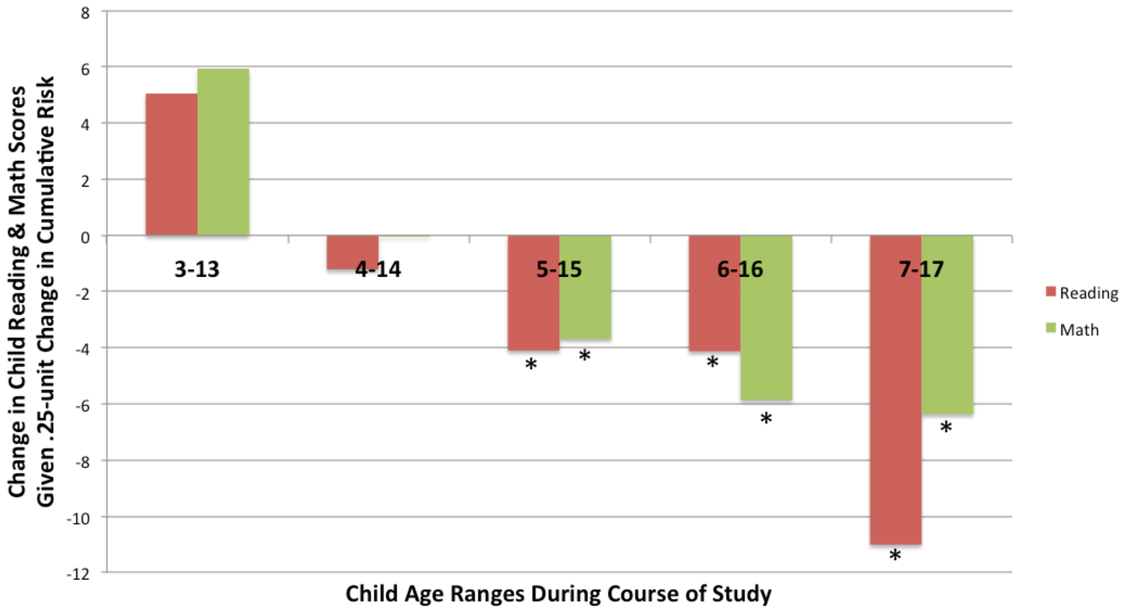
Figure 5 depicts how the associations between cumulative risk exposure and reading and math scores vary for children of different ages within the sample.

Table 14. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Cumulative Risk and Child Age at Wave 1

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Cumulative Risk	1.19 (0.79)+	20.20 (11.21)+	23.75 (13.15)+	0.99 (0.98)	0.95 (0.86)
Log of Income	0.02 (0.03)	0.25 (0.52)	0.04 (0.08)	0.02 (0.03)	0.01 (0.03)
# of Siblings	0.47 (0.09)***	12.57 (1.72)***	6.88 (1.18)***	0.35 (0.14)*	0.41 (0.12)**
Partner Status	0.02 (0.20)	-0.66 (3.41)	-2.05 (2.32)	-0.08 (0.31)	-0.27 (0.24)
Other Adults in Home	-0.01 (0.09)	-2.94 (1.80)	-0.62 (1.27)	0.00 (0.13)	-0.25 (0.14)+
Parent Ed	0.05 (0.06)	1.78 (1.18)	1.31 (0.87)	-0.01 (0.09)	-0.08 (0.07)
Employed	0.36 (0.22)	5.53 (3.52)	3.23 (2.71)	0.36 (0.41)	0.63 (0.30)*
Welfare	0.64 (0.31)	-0.05 (5.78)	-1.67 (4.01)	0.26 (0.42)	0.46 (0.34)
Public Housing	0.03 (0.27)	-1.39 (4.68)	-3.14 (3.51)	-0.42 (0.47)	-0.19 (0.33)
Food Stamps	-0.43 (0.20)*	-10.18 (3.16)**	-5.50 (2.38)*	-0.85 (0.35)*	-0.41 (0.29)
Wave/Time (in years)	0.46 (0.01)***	13.69 (0.24)***	9.48 (0.17)***	-0.11 (0.02)***	0.09 (0.02)***
Intercept	-0.96 (2.17)	352.70 (34.72)***	415.95 (21.32)***	4.15 (2.37)+	1.66 (1.94)
Cumulative Risk X Age Four	-1.22 (0.63)*	-25.30 (11.79)*	-23.48 (7.53)**	-0.97 (1.17)	-2.02 (1.08)+
Cumulative Risk X Age Five	-2.02 (0.62)***	-35.59 (11.91)**	-37.72 (8.43)***	0.65 (1.15)	-0.65 (1.07)
Cumulative Risk X Age Six	-1.48 (0.70)*	-35.07 (12.94)**	-45.71 (7.82)***	0.63 (1.22)	-0.49 (1.02)
Cumulative Risk X Age Seven	-1.97 (0.63)**	-61.10 (12.54)***	-45.92 (7.86)**	1.30 (1.47)	1.04 (1.10)
CR Estimate at Age 4	-0.01 (0.41)	-4.84 (5.60)	-0.18 (3.51)		
CR Estimate at Age 5	-1.20 (0.37)**	-16.40 (6.42)*	-14.71 (4.53)**		
CR Estimate at Age 6	-0.34 (0.55)	-16.40 (7.89)*	-23.40 (4.22)***		
CR Estimate at Age 7	-0.91 (0.46)*	-44.04 (8.85)***	-25.43 (5.17)***		

Note. Children Age 3 are the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 5. Associations between Cumulative Risk and Reading and Math Scores by Child Age at Wave 1



* $p < .05$

Mediation moderation models were again considered in order to examine whether changes in cumulative risk mediated the moderated within-child effects of income by child age. Coefficients and standard errors for moderated income effects with and without the respective interaction term for cumulative risk in the model are presented in Table 15. The residual, direct, moderated effect of income (income x child age) when cumulative risk is in the model is only minimally, if at all, reduced in value when compared to the direct, moderated effect of income when cumulative risk is not included in the model. These analyses indicated that the varied effects between changes in income and child working memory, reading, and math skills by child age were not explained by differences with respect to changes in cumulative risk by age.

Table 15. Direct and Indirect (through Cumulative Risk Exposure) Moderated Effects of Income by Child Age at Wave 1 on Child Outcomes

	Income Only + Controls	Cumulative Risk Exposure Added	
	Direct Income X Child Age	*Indirect Income X Child Age*	*Cumulative Risk X Child Age*
Working Memory	-0.05 (0.02)**	-0.05 (0.02)**	0.00 (0.00)
Reading	-1.82 (0.35)***	-1.80 (0.35)***	0.02 (0.14)
Math	-1.35 (0.24)***	-1.33 (0.24)***	0.02 (0.12)
Externalizing	0.04 (0.03)	n/a	n/a
Internalizing	0.00 (0.02)	n/a	n/a

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Variations in Associations by Race/Ethnicity

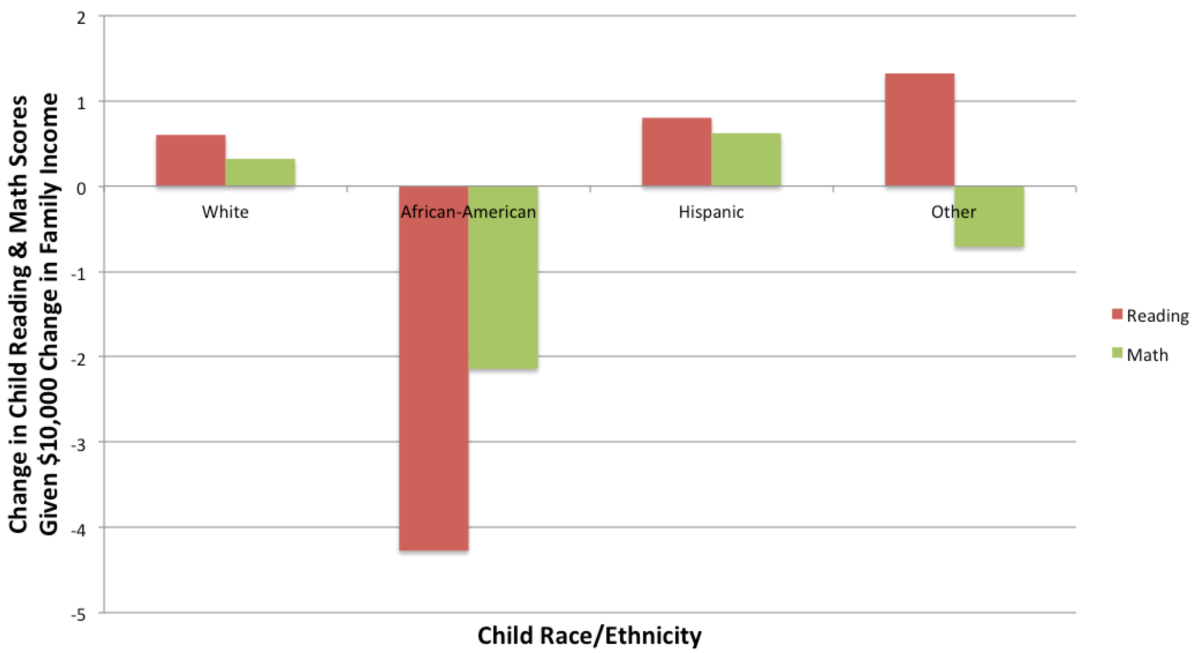
A fourth set of models investigated whether the estimated within-child associations between income, cumulative risk, and child outcomes varied by racial/ethnic groups. First, the interaction between family income and child race/ethnicity was included in models examining associations between family income and child outcomes. Results for this set of models are presented in Table 16. Associations between income and child reading and math achievement were found to differ significantly for African-American versus White children. While increases in family income were related (though not significantly) with improved reading and math scores for White children, similar increases in income were related (though again, not significantly) to diminished reading and math scores for African-American children. Figure 6 depicts how the associations between income and reading and math scores vary for White, African-American, and Hispanic children, and children of other ethnicities at the lower end of the income distribution.

Table 16. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Race/Ethnicity on Child Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Log of Income	0.02 (0.03)	0.60 (0.55)	0.32 (0.30)	0.01 (0.03)	0.01 (0.03)
# of Siblings	0.48 (0.09)***	13.02 (1.57)***	6.99 (1.18)***	0.39 (0.14)**	0.42 (0.12)
Partner Status	0.04 (0.20)	-0.49 (3.12)	-1.26 (2.35)	-0.13 (0.31)	-0.28 (0.25)
Other Adults in Home	-0.01 (0.09)	-2.61 (1.48)+	-0.42 (1.25)	-0.01 (0.13)	-0.25 (0.14)+
Parent Ed	0.06 (0.07)	1.85 (1.09)	1.47 (0.90)	-0.01 (0.09)	-0.08 (0.07)
Employed	0.36 (0.22)+	6.13 (3.35)+	3.60 (2.71)	0.35 (0.41)	0.63 (0.30)*
Welfare	0.69 (0.31)+	3.96 (5.44)	-0.23 (4.08)	0.08 (0.44)	0.38 (0.35)
Public Housing	0.07 (0.29)	-0.71 (4.58)	-2.21 (3.72)	-0.41 (0.47)	-0.20 (0.34)
Food Stamps	-0.44 (0.20)*	-11.61 (2.71)***	-6.04 (2.37)*	-0.83 (0.34)*	-0.40 (0.29)
Wave/Time (in years)	0.46 (0.01)***	13.55 (0.18)***	9.39 (0.14)***	-0.09 (0.02)***	0.10 (0.02)***
Intercept	-0.49 (2.24)	368. 31 (37.46)***	428.50 (25.38)***	6.23 (2.72)*	2.12 (2.31)
Income X African-American	-0.10 (0.09)	-4.74 (2.33)*	-3.03 (1.32)*	-0.08 (0.14)	-0.01 (0.14)
Income X Hispanic	-0.03 (0.11))	-0.07 (2.01)	-0.31 (1.69)	-0.15 (0.16)	-0.01 (0.10)
Income X Other	0.08 (0.10)	0.39 (1.46)	-0.09 (1.15)	0.16 (0.16)	0.00 (0.08)
Income Effects for African-Americans		-4.27 (2.19)+	-2.14 (1.30)		
Income Effects for Hispanics		0.80 (1.88)	0.62 (1.61)		
Income Effects for Other		1.32 (1.18)	-0.71 (0.92)		

Note. White is the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 6. Associations between Income and Reading and Math Scores for White, African-American, Hispanic, and Other Race Children



Note. Income estimates are for families at the lower end of the income distribution. Because a log transformation of income was used, a $10,000 change in income was associated with smaller changes in scores for families at the mean or above on income (i.e., $52,600).
* $p < .05$

Next, the interaction between changes in family income and race/ethnicity was included in models examining within-child associations between family income and cumulative risk. Results are presented in Table 17. The association between family income and cumulative risk did not differ by ethnicity, indicating that changes in income predicted changes in risk for all races fairly equally.

Table 17. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Income and Race/Ethnicity on Cumulative Risk

Time-Varying Variables	**Cumulative Risk**
Log of Income	-0.14 (0.05)*
# of Siblings	0.05 (0.01)***
Partner Status	-0.06 (0.02)*
Other Adults in Home	0.01 (0.01)
Parent Ed	0.01 (0.01)
Employed	0.01 (0.02)
Welfare	-0.07 (0.04)+
Public Housing	0.00 (0.03)
Food Stamps	0.05 (0.02)*
Wave/Time (in years)	0.02 (0.00)***
Intercept	0.67 (0.18)***
Income X African-American	-0.20 (0.13)
Income X Hispanic	-0.39 (0.21)+
Income X Other Race	0.09 (0.15)

Note. White is the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

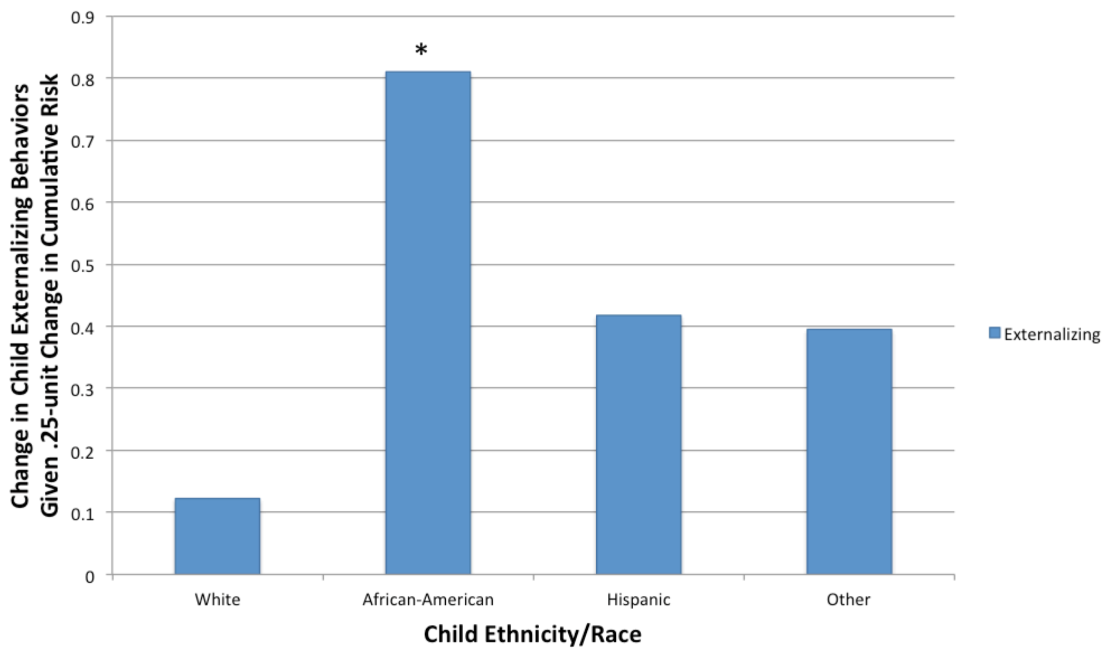
Finally, the interaction between cumulative risk exposure and race/ethnicity was included in models examining within-child associations between cumulative risk and child outcomes. These results are presented in Table 18. Associations between cumulative risk and externalizing behaviors were different for African-American children in comparison to White children (the omitted group). Changes in cumulative risk were not significantly associated with changes in externalizing for White children, Hispanic children, or children of other races/ethnicities. Changes in cumulative risk, however, were significantly associated with changes in externalizing behaviors for African-American children. For African-American children, 0.25-point decrease in risk was associated with a 0.81-point decrease in externalizing behaviors (.20 SD). Figure 7 depicts how the associations between cumulative risk exposure and externalizing behaviors vary by child race/ethnicity.

Table 18. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Cumulative Risk and Race/Ethnicity on Child Outcomes

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Cumulative Risk	-0.24 (0.31)	-13.69 (4.16)**	-6.89 (2.85)*	0.49 (0.46)	-0.10 (0.42)
Log of Income	0.02 (0.03)	0.27 (0.52)	0.03 (0.63)	0.02 (0.03)	0.01 (0.03)
# of Siblings	0.49 (0.10)***	13.30 (1.77)***	7.43 (1.20)***	0.35 (0.14)*	0.39 (0.12)
Partner Status	0.01 (0.20)	-1.28 (3.52)	-2.38 (2.40)	-0.13 (0.31)	-0.29 (0.25)
Other Adults in Home	0.00 (0.09)	-2.79 (1.77)	-0.44 (1.26)	0.01 (0.14)	-0.23 (0.13)+
Parent Ed	0.06 (0.07)	1.85 (1.21)	1.48 (0.91)	-0.02 (0.10)	-0.08 (0.07)
Employed	0.36 (0.22)	5.15 (3.49)	3.29 (2.70)	0.30 (0.40)	0.60 (0.30)*
Welfare	0.68 (0.32)*	1.60 (6.07)	-0.06 (4.14)	0.38 (0.42)	0.50 (0.34)
Public Housing	0.04 (0.28)	-0.70 (4.67)	-2.65 (3.55)	-0.36 (0.46)	-0.17 (0.32)
Food Stamps	-0.41 (0.20)*	-9.37 (3.24)**	-5.15 (2.50)*	-0.89 (0.36)*	-0.46 (0.29)
Wave/Time (in years)	0.47 (0.01)***	13.72 (0.24)***	9.51 (0.17)***	-0.12 (0.02)***	0.09 (0.02)***
Intercept	-1.11 (2.16)	348.23 (34.59)***	410.41 (21.43)***	4.12 (2.37)*	1.70 (1.94)
Cumulative Risk X African-American	-0.13 (0.49)	7.88 (7.09)	0.98 (6.49)	2.77 (0.74)***	1.27 (0.79)
Cumulative Risk X Hispanic	0.50 (0.75)	-1.73 (15.87)	-1.88 (9.62)	1.64 (1.58)	2.02 (1.37)
Cumulative Risk X Other	0.59 (1.11)	24.63 (17.64)	0.68 (12.50)	1.24 (1.68)	0.55 (1.35)
CR Estimate for African-Americans				3.24 (0.61)***	
CR Estimate for Hispanics				1.67 (1.59)	
CR Estimate for Other				1.58 (1.61)	

Note. White is the omitted group.
*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 7. Associations between Cumulative Risk and Externalizing Behaviors by Child Race/Ethnicity



* *p* < .05

Once again, mediation moderation models investigated whether changes in cumulative risk mediated the moderated within-child effects of income by child race/ethnicity. Coefficients and standard errors for moderated income effects with and without the respective interaction term for cumulative risk in the model are presented in Table 19. The residual, direct, moderated effect of income (income x child race/ethnicity) when cumulative risk is in the model is only minimally, if at all, reduced in value when compared to the direct, moderated effect of income when cumulative risk is not included in the model. These analyses indicated that the varied effects between changes in income and child reading and math skills by child race/ethnicity were not explained by differences with respect to changes in cumulative risk by child race/ethnicity.

Table 19. Direct and Indirect (through Cumulative Risk Exposure) Moderated Effects on Income by Child Race/Ethnicity on Child Outcomes

	Income Only + Controls			Cumulative Risk Exposure Added					
	Direct Moderated Effect of Income			*Direct Moderated Effect of Income*			*Estimated Indirect Moderated Effect of Income*		
	By African-American	*By Hispanic*	*By Other*	*By African-American*	*By Hispanic*	*By Other*	*By African-American*	*By Hispanic*	*By Other*
Working Memory	-0.10 (0.09)	-0.03 (0.11)	0.08 (0.10)	n/a	n/a	n/a	n/a	n/a	n/a
Reading	-4.74 (2.33)*	-0.07 (2.01)	0.39 (1.46)	-4.80 (2.35)*	-0.27 (1.95)	0.10 (1.50)	-0.06 (1.71)	-0.20 (6.21)	0.29 (2.64)
Math	-3.03 (1.32)*	-0.31 (1.69)	-0.09 (1.15)	-3.10 (1.33)*	-0.45 (1.65)	-0.06 (1.15)	-0.07 (1.33)	-0.14 (3.76)	0.03 (2.09)
Externalizing	-0.08 (0.14)	-0.15 (0.16)	0.16 (0.16)	n/a	n/a	n/a	n/a	n/a	n/a
Internalizing	-0.01 (0.14)	-0.01 (0.10)	0.00 (0.08)	n/a	n/a	n/a	n/a	n/a	n/a

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Variations in Associations by Initial Cumulative Risk Level

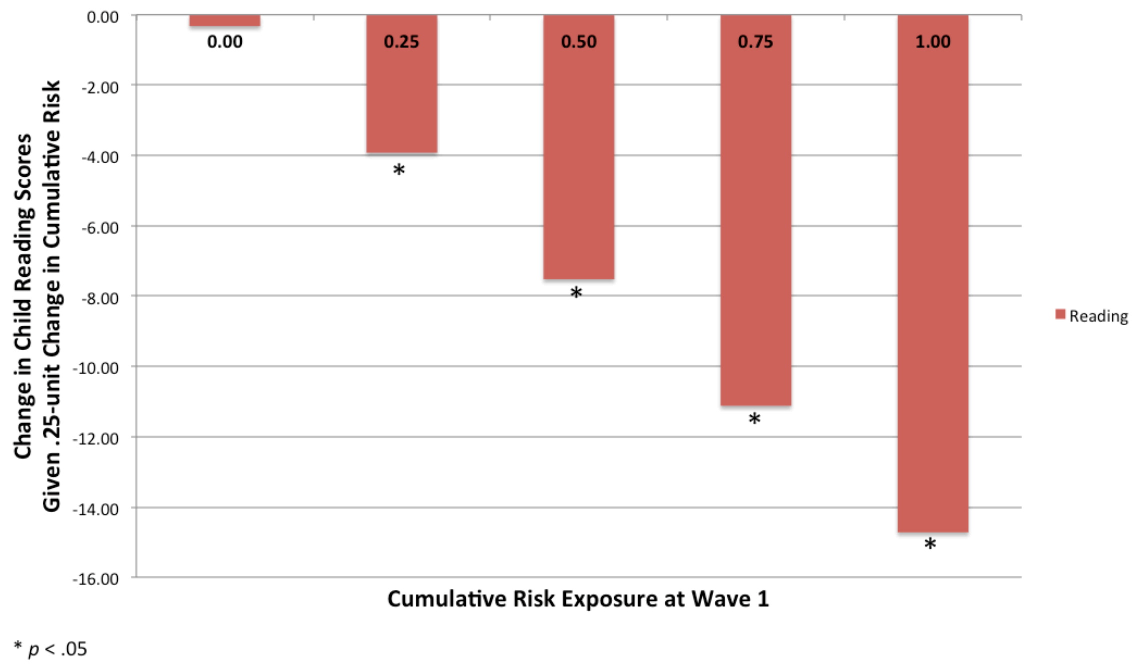
In addition to the three moderators considered in all of the previous sets of analyses, a fourth moderator was considered in examining the associations between cumulative risk and child outcomes in order to investigate whether changes in cumulative risk mattered more for those who were at high risk at the start of the study (Wave 1). This following set of models included the interaction between cumulative risk exposure and initial risk level. Coefficients and standard errors for this model are presented in Table 20. There were significant interactions between changes in cumulative risk and initial risk level on reading achievement. The higher the initial level of cumulative risk (at Wave 1), the more those changes in risk mattered with respect to reading achievement. For families who were high risk in all four domains (economic strain, neighborhood, physical home environment, and psychological home environment), a 0.25-point decrease in risk (which is the equivalent of moving from high to low risk in any one domain) was associated with a 14.27 increase in reading score (.5 SD, or more than a average year's growth). Figure 8 depicts how the associations between cumulative risk exposure and readings scores vary by initial level of risk.

Table 20. Regression Coefficients from Fixed Effects Models Examining Interaction between Changes in Cumulative Risk and Risk Level at Wave 1

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Cumulative Risk	0.18 (0.31)	-1.30 (5.63)	-3.25 (3.87)	0.94 (0.52)+	0.56 (0.49)
Log of Income	0.02 (0.03)	0.24 (0.52)	0.06 (0.29)	0.02 (0.03)	0.01 (0.03)
# of Siblings	0.49 (0.09)***	13.12 (1.72)***	7.39 (1.21)***	0.34 (0.14)*	0.40 (0.12)**
Partner Status	0.00 (0.20)	-1.25 (3.48)	-2.45 (2.39)	-0.06 (0.31)	-0.26 (0.24)
Other Adults in Home	-0.01 (0.09)	-2.82 (1.75)	-0.46 (1.26)	-0.01 (0.13)	-0.25 (0.14)+
Parent Ed	0.06 (0.07)	2.01 (1.24)	1.50 (0.92)	-0.02 (0.10)	-0.08 (0.07)
Employed	0.37 (0.22)+	5.72 (3.49)	3.34 (2.69)	0.35 (0.40)	0.63 (0.30)*
Welfare	0.69 (0.32)*	1.29 (5.90)	-0.27 (4.13)	0.21 (0.42)	0.40 (0.36)
Public Housing	0.05 (0.28)	-0.94 (4.73)	-2.66 (3.67)	-0.434 (0.47)	-0.20 (0.34)
Food Stamps	-0.40 (0.20)+	-9.26 (3.21)**	-5.01 (2.49)*	-0.88 (0.35)*	-0.41 (0.29)
Wave/Time (in years)	0.46 (0.01)***	13.66 (0.24)***	9.48 (0.17)***	-0.11 (0.02)***	0.09 (0.02)***
Intercept	-1.07 (2.18)	349.56 (34.87)***	411.62 (21.57)***	4.27 (2.39)+	1.89 (1.95)
Cumulative Risk X Risk at Wave 1	-1.98 (1.41)	-57.57 (21.75)**	-22.04 (17.15)	1.75 (2.22)	-0.94 (2.21)

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Figure 8. Associations between Cumulative Risk and Reading Scores by Initial Level of Risk at Wave 1



Additional Analyses

To check the robustness of these findings, primary analyses were also conducted using fixed effects structural equation modeling (SEM) in Stata 13.1 (StataCorp, 2013). These analyses used unimputed data in conjunction with SEM's full information maximum likelihood (FIML) option to address missing data. Not all of the analyses could be run using SEM due to difficulties with convergence when multiple interaction terms were added to the models. However, the results for the main effects models were generally quite comparable to those found using traditional fixed effects regression models with imputed data, with the only difference being that the estimate for within-child associations between cumulative risk and internalizing became significant in the

SEM models. A description of the analytic technique and results for these main effects models can be found in Appendix C.

In addition to checking the robustness of the fixed effects regression model findings, structural equation modeling also offered an opportunity to fairly easily examine whether changes in income and/or changes in cumulative risk may have a lagged effect on changes in child outcomes, as suggested by previous research (Thomson, Dearing, & Coley, unpublished). For the first set of these "lagged" models, changes in income (and time-varying covariates) between Waves 1 and 2 were used to predict changes in child outcomes between Waves 2 and 3. The second set of lagged models adds a path in which changes in income between Waves 1 and 2 predict changes in cumulative risk between Waves 1 and 2, and a path in which changes in cumulative risk between Waves 1 and 2 predict changes in child outcomes between Waves 2 and 3. More details about the analytic technique and conceptual models can be found in Appendix D. The disadvantage of these lagged models are that there are effectively only two time points in these models. Nonetheless, they allow for the exploration of the possibility that within-child changes in income and/or cumulative risk may have a delayed or more long-term effect on child outcomes, and they additionally address issues of directionality of associations.

Table 21 displays the unstandardized parameter estimates and standard errors for the set of models that examined the within-child associations between family income and child working memory, reading and math skills, and externalizing and internalizing behaviors five years later. The lagged models explained more of the respective variances in working memory, reading and math scores, and externalizing and internalizing behaviors than the non-lagged models. Results indicate that while the unstandardized coefficients for the lagged models are smaller in magnitude to those in the models that examined concurrent changes in outcomes, the standard errors are much smaller in the lagged models, resulting in greater standardized parameters and, thus, larger effect sizes. The within-child associations between family income and reading achievement five years later were significant, but the effect size (standardized coefficient) was very small, at 0.06. Within-child associations between family income and working memory, math achievement, and externalizing and internalizing behaviors five years later were not significant.

Table 21. Unstandardized Coefficients from Structural Equation Fixed Effects Models Examining Associations between Changes in Income and Changes in Child Cognitive, Achievement, and Socioemotional Outcomes Five Years Later

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Log of Income	0.00 (0.00)	0.06 (0.02)**	0.04 (0.03)	0.00 (0.01)	0.00 (0.00)
# of Siblings	0.03 (0.06)	0.38 (0.53)	0.33 (0.43)	0.04 (0.11)	-0.02 (0.10)
Partner Status	0.19 (0.22)	2.08 (1.88)	0.17 (1.93)	-0.51 (0.45)	-0.25 (0.35)
Other Adults in Home	-0.79 (0.29)**	-2.17 (1.82)	-2.72 (1.80)	0.39 (0.55)	1.10 (0.47)*
Parent Ed	0.11 (0.03)***	2.29 (0.29)***	2.06 (0.25)***	-0.07 (0.05)	-0.08 (0.04)+
Employed	0.00 (0.20)	4.88 (1.91)*	1.36 (1.44)	0.05 (0.38)	-0.18 (0.29)
Welfare	-0.11 (0.31)	-1.33 (2.70)	-4.00 (2.36)+	-0.09 (0.75)	-0.01 (0.46)
Public Housing	-0.44 (0.32)	-2.93 (2.19)	-1.87 (1.83)	1.60 (0.80)*	-0.03 (0.48)
Food Stamps	0.25 (0.25)	1.10 (1.80)	-0.27 (1.57)	0.91 (0.41)*	0.51 (0.24)
Intercept	3.53 (0.41)***	468.73 (4.45)***	478.75 (3.68)***	6.75 (0.89)***	4.66 (0.70)***
CD	.68	.89	.86	.80	.75

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Results for the lagged fixed effects structural equation mediation model indicated that changes in family income were significantly associated with changes in cumulative risk ($\beta = -0.06$, SE = 0.01, $p < .001$), with increases in family income predicting decreases in cumulative risk. The effect size (standardized coefficient) for the associations between changes in income and changes in cumulative risk in the lagged model (-0.21) is somewhat smaller than that of the non-lagged model (-0.31). Table 22 displays the unstandardized parameter estimates from the structural equation models that simultaneously examined the effects of family income, cumulative risk and time-varying covariates on child working memory, reading and math skills, and externalizing and internalizing behaviors five years later. Similar to the results reported for the fixed effects regression analyses, decreases in cumulative risk were significantly associated with increases in children's reading and math skills and decreased externalizing behaviors. In the lagged structural equation models (and in the non-lagged structural equation models), decreases in cumulative risk were also significantly associated with decreased internalizing behaviors.

Table 22. Unstandardized Coefficients from Structural Equation Fixed Effects Models Examining Associations between Changes in Income, Changes in Cumulative Risk, and Changes in Child Cognitive, Achievement, and Socioemotional Outcomes Five Years Later

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Cumulative Risk	-0.50 (0.29)+	-5.15 (2.85)+	-6.89 (2.16)***	1.95 (0.59)**	1.76 (0.48)***
Log of Income	0.00 (0.00)	0.05 (0.02)*	0.03 (0.03)	0.00 (0.01)	0.00 (0.00)
# of Siblings	0.04 (0.06)	0.45 (0.53)	0.42 (0.42)	0.01 (0.11)	-0.05 (0.09)
Partner Status	0.16 (0.23)	1.86 (1.92)	-0.11 (1.93)	-0.44 (0.45)	-0.19 (0.35)
Other Adults in Home	-0.83 (0.29)**	-2.61 (1.77)	-3.31 (1.89)+	0.49 (0.57)	1.19 (0.48)*
Parent Ed	0.11 (0.03)***	2.26 (0.29)***	2.00 (0.35)***	-0.05 (0.05)	-0.07 (0.04)
Employed	-0.02 (0.20)	4.74 (1.94)*	1.15 (1.43)	0.06 (0.39)	-0.17 (0.29)
Welfare	-0.13 (0.31)	-1.48 (2.69)	-4.21 (2.32)+	0.00 (0.77)	0.08 (0.47)
Public Housing	-0.40 (0.33)	-2.53 (2.16)	-1.33 (1.76)	1.59 (0.82)+	-0.07 (0.49)
Food Stamps	0.27 (0.25)	1.26 (1.81)	-0.03 (1.60)	0.83 (0.43)+	0.43 (0.36)
Intercept	3.70 (0.42)***	470.21 (4.64)***	480.82 (3.70)***	6.19 (0.90)***	4.17 (0.70)***
CD	.80	.93	.91	.86	.84

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Effect sizes (standardized coefficients) for the associations between income and child academic outcomes and for the associations between cumulative risk and child academic outcomes were generally larger in the lagged models than the non-lagged models. Effect sizes for the associations between income and child socioemotional outcomes and for the associations between cumulative risk and child socioemotional outcomes were generally larger in the non-lagged models than the lagged models. A comparison of these effects sizes is presented in Table 23.

Table 23. Standardized Coefficients for Associations between Changes in Income and Changes in Risk and Concurrent Child Outcomes and Child Outcomes Five Years Later

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Concurrent Outcomes					
Risk	-0.03	-0.05*	-0.05*	0.17***	0.16***
Income	0.07	0.03	0.02	-0.04	-0.02
Lagged Outcomes					
Risk	-0.06+	-0.05+	-0.09***	0.11***	0.13***
Income	0.05	0.05*	0.04	0.02	0.03

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Finally, direct and indirect effects of income, through cumulative risk, were calculated for child working memory, reading and math achievement, and externalizing and internalizing behaviors five years later. Coefficients and standard errors for lagged income effects with and without cumulative risk in the model are presented in Table 24. Results indicate small but significant indirect effects of changes in income through changes in cumulative risk on math achievement, externalizing scores and internalizing scores five years later. Indirect effects of changes in income through changes in cumulative risk on working memory and reading skills five years later approached significance.

Table 24. Direct and Indirect (through Cumulative Risk Exposure) Effects of Income on Lagged Child Outcomes

	Income Only + Controls	Cumulative Risk Exposure Added	
	Direct Effect of Income	*Direct Effect of Income*	*Indirect Effect of Income*
Working Memory	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)+
Reading	0.06 (0.02)**	0.05 (0.02)*	0.02 (0.01)+
Math	0.04 (0.03)	0.03 (0.03)	0.02 (0.01)**
Externalizing	0.00 (0.01)	0.00 (0.01)	-0.01 (0.00)**
Internalizing	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)**

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Summary of Results

In sum, fixed effects regression models indicated that for the sample as a whole, changes in family income did not have direct effects on child outcomes, but did have significant indirect effects, through changes in cumulative risk exposure, on children's reading and math achievement and externalizing behaviors. Changes in family income had stronger associations with children's working memory and reading skills for children from families with lower initial incomes, and stronger associations with all cognitive/academic outcomes for child in the younger "age cohorts." Associations between changes in family income and academic achievement were significantly weaker for African-American children. However, changes in cumulative risk did not mediate these moderated within-child associations.

Changes in family income were associated with changes in cumulative risk exposure for the sample as a whole; and changes in cumulative risk, in turn, were associated with changes in children's math and reading achievement and externalizing behaviors for the sample as a whole. The within-child associations between income and cumulative risk were stronger for families whose initial incomes were at the lower end of the income distribution, but did not vary across age cohorts or race/ethnicities. And the moderated associations between cumulative risk and child outcomes exhibited different patterns than those seen in the moderated associations between income and child outcomes. Changes in cumulative risk had stronger associations with changes in children's cognitive/academic outcomes for older children. Changes in cumulative risk also mattered more for, with respect to reading achievement, for children who experienced high initial levels of risk. In addition, variation in the strength of associations was seen between changes in cumulative risk and children's socioemotional outcomes. Specifically, changes in cumulative risk had stronger associations with changes in externalizing behaviors for African-American children, and with changes in both externalizing and internalizing behaviors children from families whose initial incomes were at the lower end of the income distribution.

Results from SEM models (see Appendix C), lagged models (see above and Appendix D), and alternate model specifications (see Appendix E) were generally consistent with these findings. Hausman tests also confirmed the appropriateness of fixed effects over random effects models (see Appendix F).

CHAPTER 4: DISCUSSION

A growing body of work in the fields of neuroscience and developmental psychology has highlighted the neurobiological consequences of stress on children's developing brains, with evidence that exposure to an array of contextual stressors helps explain why children growing up poor are at risk for underachievement and psychosocial maladjustment (Blair et al., 2013; Blair et al., 2011; Evans & Kim, 2013; Gunnar & Vasquez, 2001; McEwen, 2006; Suor et al., 2015). This work provides a framework for understanding the experience of poverty as exceptionally harmful to child growth because of the cumulative effects of exposure to multiple stress factors at various levels of children's psychosocial milieu (Deater-Deckard et al. 1998, Evans, 2004; McLoyd, 1998). The present study added to this burgeoning field by offering some of the first evidence on two critical questions: (1) to what extent do changes in family economics relate to changes in cumulative risk exposure and, in turn, relate to changes in child outcomes (e.g., do improving economic circumstances predict reductions in cumulative risk and, in turn, improvements in child achievement and well-being?) and (2) at what time during child growth, under what economic conditions, and for which children are cumulative stress pathways most robustly evident?

On the whole, findings from the present study were consistent with the cumulative stress model. On average, the estimated direct effects of changes in family income (i.e., prior to examining mediation or moderators) were not significant for changes in child outcomes. Yet, changes in income were, for the sample as a whole, indirectly related via changes in cumulative risk exposure: increases in income predicted decreases in cumulative risk exposure and, in turn, decreases in cumulative risk predicted improvements in achievement and declines in externalizing behavior problems. And, as expected, these relations were moderated by child age, initial level of family income, and initial level of cumulative risk. Specifically, the estimated direct effects of changes in family income on changes in child outcomes were largest for children whose families were at the lower end of the income distribution at the start of the study and for the younger children in the sample. In addition, changes in cumulative risk were most strongly associated with changes in child outcomes for those experiencing high levels of risk at the start of the study and (unexpectedly) for older children in the sample.

Below, results according to each major analytic goal of the study are discussed in greater detail. In so doing, extensions and validations of (or challenges to) the existing knowledge on poverty and cumulative risk exposure are discussed. Special attention is given to that fact that understanding the consequences of *changes* in family economics and exposure to stress-producing contexts, and developmental timing of these changes, is critical to the field's cumulative knowledge on why, how, and under what conditions context and risk matter for child wellbeing. In addition, the importance of these results for guiding interventions and policy is underscored, with an emphasis on leveraging protective factors that may induce the greatest positive impact on disadvantaged children's lives.

A Cumulative Risk Model Linking Changes in Income with Changes in Child Outcomes: Direct and Indirect Effects

The first overarching goal of this dissertation research was to examine whether changes in exposure to cumulative risk/stressors provided an indirect path linking changes in family income and changes in children's cognitive, academic, and socioemotional outcomes. This mediation model was examined, first, by estimating the direct effects of changes in income on child outcomes and, second, by estimating indirect effects via changes in cumulative risk. Somewhat surprisingly, estimates of the direct effects[2] of changes in income on changes in child outcomes were null when estimated for the sample as a whole. Indirect effects were evident, however, given robust relations between (a) changes in income and changes in cumulative stress and (b) changes in cumulative stress and changes in child outcomes.

Direct effects. Drawing on evidence from previous research, it was expected that changes in family income would be associated with changes in child cognitive/academic outcomes and changes in child socioemotional outcomes (Dahl & Lochner, 2005, 2012; Dearing, McCartney, & Taylor, 2009; Duncan, Morris, & Rodrigues, 2011; Zachrisson & Dearing, 2015). However, in the present study, while direct associations between changes in family income and changes in child cognitive/academic outcomes were in the expected direction—that is, increases in family income were generally associated with improved cognitive and academic outcomes, and decreases in income associated with diminished growth in these skills—they were not significant for the sample as a whole. While somewhat surprising given the past evidence of links between income changes and child outcome changes, the results are not entirely inconsistent with those of Currie's (1995) analyses of the negative-income-tax experiments in the 1970's. In this analysis, Currie did not find across-the-board average income effects on school achievement. Instead, income effects were found in some sites but not others, with the largest effects found at

[2] The term "direct effect" is used to describe the total relation between income and child outcomes prior to estimating the mediating role of cumulative risk; it is not intended to imply that there are (from a conceptual standpoint) truly unmediated effects of income on child outcomes.

one of the poorest sites, suggesting (as the present research also does) that income level may moderate links between family income and child development, perhaps in ways not easily detectable simply using the semi-log approach (e.g., timing of poverty or more complex non-linearity might come into play).

Indirect effects. Despite the absence of direct effects of income, changes in a family's income were indirectly associated with child reading and math achievement and externalizing behaviors. Specifically, changes in cumulative risk exposure mediated associations between income changes and child outcome changes such that income gains predicted reductions in risk and, in turn, improvements in child outcomes. These findings offer some of the first evidence of a dynamic mediation model that extends growing evidence that the harm of low income *level* is mediated by cumulative risk *level* (Deater-Deckard, Dodge, Bates, & Pettit, 1998; Evans & English, 2002; Gutman, Sameroff, & Cole, 2003; Lengua, Honorado, & Bush, 2007; Rauh et al., 2003; Thomson, Dearing, & Coley, unpublished). The fact that the present study extends this evidence to include the indirect connections between changes in income, changes in cumulative risk, and changes in child outcomes is critical in that it is consistent with the working hypothesis that both risk exposure and, in turn, child outcomes are malleable and responsive to improvement in family economic conditions. While changes in economics and contextual risk were not randomized in the present study (raising questions of potential time-varying selection effects), the ability to rule out between-child and between-family differences is encouraging from both a cause probing and policy making standpoint. Of course, practical importance depends on effect sizes, not merely statistical significance.

With regard to effect size, a $10,000 increase in income was associated with a decrease equivalent to 89% of the average between-child standard deviation in cumulative risk. This finding is in line with previous research that has demonstrated that children in poverty are not only more likely, overall, to experience individual risk factors – such as increased economic strain, neighborhood crime, physical home disorder, and family conflict – but are also more likely to accumulate multiple risk factors across a wider array of contextual risk domains (Evans & Kim, 2013; Thomson, Dearing, & Coley, unpublished). However, few studies (if any) have examined how exposure to these risk factors, either individually or combined into a summative or cumulative risk index, may *change* in response to *changes* in family income.

In addition to finding that the changes in family income predicted changes in the cumulative number of risks to which a child was exposed, across a range of domains, the present study also highlights the responsivity of some domains of risk, but not others, to changes in family income. The present study found, for example, that increases in family income were linked with decreased economic strain and physical home disorder; and, conversely, decreases in family income were linked with increases in economic strain and physical home disorder. Changes in family income were not, however, related to changes in risk related to neighborhood quality or home psychological environment, as it was measured here. This suggests that the components of risk related to economic strain and physical home conditions may be more directly and easily affected by changes in family income than, for example, moving to a better neighborhood. It also suggests that while some domains of risk may be less responsive to changes in income, the cumulative risk index was nonetheless able to capture the way in which the total number of risk factors to which a child is exposed is linked to changes in family income.

Adding to the importance of the documented links between income and cumulative risk changes, this study is the first, to the best of my knowledge, to demonstrate that *changes* in cumulative risk exposure predict changes in child outcomes. This is consistent with evidence that children who have been exposed to higher levels of cumulative risk are more likely to exhibit poorer working memory skills, lower achievement, and greater incidence of externalizing and internalizing behaviors (Evans & Kim, 2013; Evans & Schamberg, 2009; Sameroff et al., 1998; Thomson, Dearing, & Coley, unpublished). Extending this line of work, the present study found that decreases in cumulative risk were associated with improvements in children's reading and math achievement and declines in externalizing behavior problems; conversely, increases in cumulative risk predicted worsening outcomes in these areas (or, with regard to achievement, slower rates of skill growth).

It is worth noting, however, that changes in cumulative risk were not associated with changes in children's working memory or internalizing problems for the sample as a whole. With regard to working memory this may, at least in part, reflect the difficulty of detecting subtle changes in children's cognitive abilities above and beyond those associated with developmental growth over time (Hughes & Bryan, 2003), and may be further complicated by uneven spurts in the maturation of working memory skills across at different time points in a child's development (Brocki & Bohlin, 2004), as well as floor effects for children younger than 6 on simple (forward) span tests and for children younger than 9 on complex (backward) span tests (Roman, Pison, & Kronenberger, 2014). With regard to internalizing problems, it is also true that relations between income changes and behavior problems have generally been stronger for externalizing domains than internalizing, with researchers offering two points of speculation (e.g., Dearing et al., 2006): on the one hand, changes in internalizing problems may be more difficult to detect by observers –whether parents, teachers or otherwise – and, on the other hand, externalizing problems may be more closely linked with acute events, while the development of internalizing problems may be more a factor of chronic exposure to risk and less mutable in response to temporary changes. Regardless, internalizing problems was one outcome for which moderation was evident, as described below.

Before turning to moderation results, it is worth juxtaposing the null direct effects of income on child outcomes for the sample as a whole with the evident indirect effects. This may be simply a matter of the strength of the relation between income and child outcomes; for predictors that affect outcomes exclusively via indirect means (and are fairly distal to the outcomes), tests of their total effects on the outcomes are more likely to result in Type II errors than are correctly powered tests of mediated effects (MacKinnon, 2008). However, these two results, considered side-by-side, also raise the interesting possibility that there are factors, associated with increases in income, that might negatively affect children's academic outcomes and be related to increased behavior problems (or vice versa: factors associated with decreases in income and linked to improved outcomes and decrease behavior problems).

One hypothesis is that as a family's income increases, additional supports designed specifically to assist at-risk families may no longer be available or, insofar as they remain available, may involve significant financial cost. For example, as families rise out of poverty, they are no longer eligible for governmental supports and services designed specified to assist families in the direst of circumstances. While I attempted to control for exactly this phenomenon by including time-varying indices of welfare, housing, or foodstamps assistance as covariates in my models, they are not exhaustive of all such programs, such as the Earned Income Tax Credit, Child Tax Credit, Medicare, and Children's Health Insurance Program. I was also not able to control for state or community-based programs or services, or for more informal networks of support – such as extended family or friends – that may provide assistance in a range of ways when a family experiences a loss in income. The presence (or removal) of these additional sources of non-income-based financial support (as well as other forms of support, such as grandparents providing childcare, that may free up limited resources) may be associated with falling (or rising) income; and yet, they are also likely to be a positive (or negative, when removed) influence on the life and development of the child. In this way, decreases (or increases) in income may have an indirect effect, though such supports, in the opposite direction as expected. Such factors might thus obfuscate some of the direct effects of income on child outcomes in the present analyses, which were visible as significant indirect effects through cumulative risk exposure.

Moderators of Within-Child Associations between Family Income, Cumulative Risk, and Child Outcomes

The second overarching goal of the present dissertation research was to explore moderators of the relations between family income, cumulative risk, and child outcomes: that is, under what economic circumstances, at what developmental time points, and for what subpopulations do changes in family income and cumulative risk matter most?

Below, results are discussed for analyses examining whether within-child associations between family income, cumulative risk, and child outcomes are moderated by, (a) initial family income level, (b) child age, and (c) race/ethnicity as well as (d) initial level of cumulative risk. For each moderator considered, moderation of within-child associations between family income and child outcomes are discussed first, followed by discussion of moderation of within-child associations between family income and cumulative risk and moderation of within-child associations between cumulative risk and child outcomes. Lastly, possible mediation via cumulative risk of the moderated effects of income on child outcomes is discussed.

Moderation by initial family income level. As suggested by previous research (e.g., Currie, 1995; Dahl & Lochner, 2005, 2012; Dearing, McCartney, & Taylor, 2001), moderator effects investigating whether changes in family income would matter more for children from more economically disadvantaged families were examined in the present study. This strategy provided an extension of the semi-log estimation strategy. Specifically, within-child associations between family income and children's working memory and reading achievement, but not math achievement or behavioral outcomes, were strongest for families whose income was at the lower end of the income distribution during their early years of development (i.e., during Wave 1, when the children in the study ranged from 3-7 years of age). While changes in income did not predict changes in child outcomes for families whose initial income at the start of the study was at the higher end of the income distribution, increases in income significantly predicted increases in working memory and reading scores for children in families with initial incomes less than or equal to $25,000 (approximately 200% of the 1997 federal poverty level).

It is likely that families at the lower end of the income distribution are most affected by changes in income because those changes represent a much more substantial proportion of their overall income than they do for families who start out with more. Additionally, as argued by Meyer (1999), families at the lower end of the income distribution, who are just barely able to pay their bills, are less able than higher-income families to smooth out their consumption by saving for periods of unanticipated income loss or even borrowing against future anticipated income gains. The present findings support Currie's (1995) investigations of the negative income tax experiments, which found larger income effects on children's achievement at poorer sites, as well as Dahl and Lochner's (2005, 2012) examinations of changes in the Earned Income Tax Credit, which found stronger income effects on reading and math scores for children from more disadvantaged families. Together, these analyses provide a foundation of empirical evidence that programs and policies designed to supplement the income of specifically lower-income families have the potential to enhance the educational achievement of their children and diminish the income achievement gap.

It is also possible that the inclusion of *initial* family income level as a moderator is actually testing a combination of income level and child age effects: that is, whether changes in income are stronger for families who have lower incomes specifically during their children's early childhood and early elementary years (the age range of the children in the sample at Wave 1). Thus, these results may indicate not only that families at the lower end of the income distribution are most affected by changes in income (which is supported by the semi-log estimation strategy), but also that changes in income may matter more for families who are poor or low-income at this particular stage in their child's development, more specifically. As such, these findings, in combination with the child age results discussed below, provide a robust story about the importance of child age in considering the associations between family income and child outcomes.

Initial family income level was also examined as a potential moderator of within-child associations between changes in income and changes in cumulative risk. Results showed that associations between changes in income and changes in cumulative risk did vary by a family's initial income level. The same $10,000 change in family income predicted greater changes in cumulative risk for families whose initial income was at the lower end of the income distribution at the start of the study compared to families whose incomes were at the higher end of the distribution. Though the literature examining variation in these associations is sparse, this makes conceptual sense. Not only is a $10,000 increase or decrease in income a much greater proportional change in income for families at the lower end of the spectrum, but these families are also much more likely to be experiencing (or on the verge of experiencing) multiple, co-occurring contextual risks, such that a change in income is more likely to push them across the threshold-level of risk in one direction or another. By contrast, for families at the higher end of the income distribution, a change in income might be unlikely to push families across risk thresholds, if environmental changes occur within a "good enough" range of environments. For higher income families, for example, an increase in income may allow for a move to a more desirable neighborhood, but that change may not represent an improvement in neighborhood safety, if both neighborhoods are reasonably safe, as measured here.

Next, initial family income level was examined as a potential moderator of within-child associations between changes in cumulative risk and changes in child outcomes. While, again, there is very limited research on how the within-child associations between cumulative risk and children's outcomes might vary for different subpopulations, these associations were also hypothesized to be stronger for children whose families fell at the lower end of the income distribution. The present research only partially supports this hypothesis. Decreases in cumulative risk were associated with larger decreases (and increases in cumulative risk associated with larger increases) in externalizing and internalizing scores for families with lower initial incomes, compared to family with higher initial incomes, at the start of the study. However, changes in cumulative risk mattered fairly equal for all income-levels when it came to academic outcomes. An interesting direction for future research would be to examine additional factors associated with low-income contexts, such as less positive early peer interactions and/or lower-quality early care settings (Criss, Pettit, Bates, Dodge, & Lapp, 2002), that might intensify the effects of changes in cumulative risk on children's socioemotional outcomes.

Finally, the present research examined whether changes in cumulative risk mediated the moderated effects of income by initial income level. While changes in cumulative risk did mediate within-child associations between family income and child outcomes for the sample as a whole, changes in cumulative risk did not mediate the moderated effects of income. That is, differences with respect to changes in cumulative risk did not explain why changes in income mattered more, with respect to cognitive/achievement outcomes, for children from families whose income was at the lower end of the income distribution at Wave 1. This null finding suggests that while cumulative risk may explain some of the within-child associations between family income and child outcomes, other pathways play a role as well and may help to explain some of the moderated effects of income seen in the present study.

Moderation by child age at Wave 1. Additionally, the present study examined whether within-child associations between family income, cumulative risk, and child outcomes were moderated by child age at the start of the study. Results from the present study converge with and extend previous research, which has found stronger associations between family income and child achievement for younger children (Brooks-Gunn & Duncan, 1997; Duncan & Brooks-Gunn, 1997; Duncan & Brooks-Gunn, 2000; Duncan, Kalil, & Ziol-Guest, 2010; Duncan & Magnuson, 2013). For children in the present study who were 3 years old at Wave 1, a $10,000 increase in income (for those at the lower end of the income spectrum) was associated with an almost a half a year's average growth in working memory, reading and math skills. For children who were age 4-14 and 5-15 years over the course of the study, this same increase in family income was associated with reduced but still significant improvements in these skills. For children who were aged 6-16 years over the course of the study, however, an increase in income was not associated with cognitive and academic improvements.

These stronger within-child associations between family income and children's cognitive and academic skills for younger children is in line with previous research indicating that the earlier the changes in a family's economic circumstances occurs, the greater the improvement in child outcomes (Duncan et al., 1998). Nonetheless, it should be noted that the present research does not speak directly to whether changes in family income that happen in early childhood matter more than changes in family income that happen in later childhood or adolescence. Rather, the present findings indicate that changes in family income that happen during the span of time between ages 3 and 13, for example, matter more than those than those that happen during the span of time between ages 6 and 16. This suggests that child age is important in considering the associations between family income and child outcomes, and that programs and policies design to boost a family's income may be most effective when implemented earlier, rather than later, in a child's development.

Nonetheless, it was surprising to find that for children who were 7-17 years of age during the study, increases in income were associated with diminished scores, and decreases in income associated with improved scores. Why would changes across this period in a child's life have not just a diminished effect on child outcomes, but an effect in the opposite direction? A possible explanation begins with the recognition that for this particular subsample of children, we do not have a window into their family circumstances or development prior to age 7. This is particularly relevant in light of research that suggests that income effects may be strongest during a child's earliest years (Duncan et al., 1998), precisely the years for which we are lacking information for this subsample of children.

In addition, as the descriptive statistics indicate, there is considerably less variability in academic outcomes at Wave 3, and additional analyses indicate that the rate of growth in children's cognitive and academic skills (but not externalizing or internalizing behaviors) also varies by child age at Wave 1. This suggests that the later in a child's life that we are able to measure changes in their academic growth, the changes we observe are likely to be considerably smaller. It may be, then, that the moderated effects of income on child cognitive and academic outcomes by child age at Wave 1 are nonlinear, and that the negative associations seen in the present research between changes in income and changes in cognitive/academic outcomes for the oldest children in the sample are the result of imposing a linear specification (due to examining change with only three time points) on data for which a quadratic specification might be more appropriate.

Child age at Wave 1 was also examined as a potential moderator of within-child associations between family income and cumulative risk. These associations were not found to vary by child age at Wave 1, indicating that a $10,000 increase or decrease in income makes the same amount of difference in terms of changes to a family's exposure to contextual risk, regardless of a child's age. In other words, increases or decreases in income are not necessarily more likely to reduce or increase risk for children between the ages of 3-13 years than for children between the ages of 7-17 years.

Next, child age at Wave 1 was examined as a moderator of within-child associations between cumulative risk and child outcomes. Within-child associations between cumulative risk and academic achievement (but not socioemotional outcomes) were found to vary by child age at Wave 1, but not in the expected direction. Perhaps one of the most surprising findings of the present research was that changes in cumulative risk were more strongly associated with reading and math achievement for children who were older at the start of the study – that is, for children who were 7-17 years old during the course of the study, in comparison to children who were 3-13 years old during the course of the study. This finding is surprising for a number of reasons. First it goes against current thinking about the mechanisms underlying the cumulative risk model: namely, that the physiological consequences of cumulative risk may be particularly harmful early in life, when children's brains are developing more quickly and may be more sensitive to environmental influences (Sapolsky, 2004; Shonkoff & Phillips, 2000). Secondly, the present results indicated that associations between changes in income and child cognitive/academic outcomes were stronger for younger children. One would expect, if it were the case that cumulative risk mediates the associations between income and child outcomes, that we would see a similar pattern of moderation, insofar as we saw any moderation by age. Instead the present research found the opposite.

Why might this be? Several hypotheses seem plausible. First, it is worth noting that the present measure of cumulative risk is a summative index of risk at one point in time, rather than a measure of chronic risk or even average risk over an extended period of time. This distinction is important because prolonged, but not necessarily contemporaneous, acute exposure to stress is thought to lead to long-term physiological changes specifically designed to protect our systems from the damage that elevated stress hormones can have over a long period of time (Fries, Hesse, Hellhammer, & Hellhammer, 2005). In this way, prolonged risk/stress during the early childhood years may lead to larger and larger between-child differences, as they build up over time. However, it may be that contemporaneous risk exposure affects child development in ways that are more malleable (McEwen, 2004). In other words, when the risk or stressor is removed from a child's life, the affected areas of the child's brain "recover" in ways that are suggested by the present within-child models, such that changes in risk are associated with changes in outcomes.

But while the distinction between chronic and contemporaneous risk/stress exposure might begin to explain why the present research did not find stronger within-child associations for younger children, it does not explain why cumulative risk might matter more for older children. In this regard, one hypothesis is that school environments and/or peer relationships, which become more important as children age, may accentuate risk. That is, the present cumulative risk index measures risks across a range of domains but is by no means exhaustive. For instance, it may be, and is in fact quite probable, that children who experience risk/stress across any one or more of the domains included in the current measure of risk are also more likely to experience risk/stress across domains not included. That is, children who live in unsafe neighborhoods are more likely to attend schools that have characteristics or social environments that may add to a child's stress (see, e.g., Lynch, 2003). In this way, a change in neighborhood would also likely mean a change in schools and maybe even a change in peer groups, essentially multiplying the effect of the change in stress that is actually measured in the present study. This additional social-environmental stress may play an especially important role in adolescence when peer relationships and social environments become more primary (Viner et al., 2012). A related and complementary hypothesis is that the onset of puberty could accentuate the effects of stressors (Ge, Conger, & Elder, 2001). Finally, it may also be that as children age, they become more cognizant of the stressors in their lives, how their own circumstances compare to that of their peers or others, and even how these stressors may affect what opportunities are available to them in the future (which is coming ever nearer). This added cognitive element may also lead changes in risk to be accentuated in the teen years in particular.

Additionally, it may be that other pathways that have been found to mediate the association between family income and child outcomes, such as the Parental Investment

Model and the Family Stress Model, may play a greater role in early childhood, thereby minimizing the unique role of cumulative stress during these early years. Moreover, parents may be more able to protect their children from certain risk factors in their child's early years than they are when their child is older. For example, if a family lives in an unsafe neighborhood, a parent may be more able, when the child is young, to minimize his/her exposure to the extent of the crime or violence outside their home by keeping to themselves, not going outside after dark, choosing routes that bypass particular corners known for drug activity, and so forth (Rosenblatt & DeLuca, 2012). In this way, parents (or other adults in the child's life) may be more able to buffer the level of stress to which a child is exposed when they are younger, in contrast to when they are older, such that changes in cumulative risk may matter more for older children.

Cumulative risk may also matter more for older children because the effects of cumulative risk may time to appear, and thus be "lagged." This hypothesis is supported by previous research that found that compared the unique contribution of the family stress, parental investment and cumulative risk pathways (Thomson, Dearing, & Coley, unpublished). This research found that the parental investment and pathways explained concurrent variation in children's academic and socioemotional outcomes, respectively. The cumulative risk pathway, however, explained variation in children's longer term outcomes (five and ten years out).

Finally, the present research explored whether changes in cumulative risk mediated the moderated effects of income by child age at Wave 1. The present results suggest that this is not the case. Differences with respect to changes in cumulative risk did not explain why changes in income mattered more for younger children. Again, this null finding suggests that while cumulative risk may explain some of the within-child associations between family income and child outcomes, other pathways play a role as well and may explain some of the moderated effects of income seen in the present study.

Moderation by race/ethnicity. The present research further examined whether within-child associations between family income, cumulative risk, and child outcomes were moderated by child race/ethnicity. Results indicate that associations between income and child achievement did vary by race. Within-child associations between family income and child math and reading achievement were in the expected direction, though non-significant, for White, Hispanic, and children of other ethnicities; however, these associations were in the opposite direction for African-American children. Though these negative associations for African-American children were also not significant, it bears considering why increases in income are less likely to be positively related to better academic outcomes for African-American children than they are for other ethnicities. One hypothesis is that increases in income do not diminish or necessarily counteract, and may even accentuate, some of the stressors that are related to race: such as incidence of racial discrimination and profiling, daily racism microstressors, or less positive feelings of belonging or social identity (Harrell, 2000). Future research is needed to further investigate such race-related stressors, and particularly whether some of these stressors might be accentuated by factors or contexts that might also change as income changes. These factors should be be kept in mind when considering implementing policies and programs with populations that include minority children.

With respect to whether within-child associations between family income and cumulative risk might vary by child race/ethnicity, the present research indicates that increases or decreases in income are not necessarily more likely to reduce or increase cumulative risk for children of different races/ethnicities. In other words, changes in income are associated with changes in cumulative risk for minority populations to a similar extent as they are for nonminority populations. These findings do not necessarily contradict previous research that has suggested that race may play a role in the degree to which differences in income are related to certain indicators of contextual risk (Chetty & Hendren, 2015; Reardon, Fox & Townsend, 2015). It may be that other unmeasured aspects of risk are affected differently by race.

Next, with respect to question of whether race moderated associations between cumulative risk and children's outcomes, the present research found that decreases in cumulative risk were associated with larger decreases (and increases in cumulative risk associated with larger increases) in externalizing scores for African-American children. That is, changes in cumulative risk mattered more for African-American children with respect to externalizing behaviors. Indeed, changes in cumulative risk were not associated with changes in externalizing behaviors for children of any other race. These findings support previous research (American Psychological Association, 2016; Hicken et al., 2014), that suggest increases in cumulative risk compound stressors related to informal but often all-too-tangible barriers to success, unequal opportunities, prejudice and, for African-American, racism. Such race-related stressors have been found to be particularly salient in the risk for violent behaviors among African Americans transitioning into young adulthood (Estrada-Martinez, Caldwell, Bauermeister, & Zimmerman, 2012).

Finally, the present research explored whether changes in cumulative risk mediated the moderated effects of income by child race. It was expected that changes in cumulative risk might partially explain the less positive associations between family income and child academic outcomes for African-American children. The present results suggest that this is not the case. That is, differences with respect to changes in cumulative risk did not explain why changes in income mattered less (or trended in the opposite direction) for African-American children, suggesting that there are other factors beyond those included in the present study that are at play.

Moderation by initial level of cumulative risk. An additional moderator of within-child associations between cumulative risk and child outcomes was also examined: namely, initial level of cumulative risk. Though there is no extant literature on whether associations between cumulative risk and child outcomes might vary for children who face high vs. low levels of risk across multiple domains in their early years, it was expected that changes in cumulative risk would matter more for children who faced higher cumulative risk at the start of the study. The present research supported this hypothesis for some, but not all, child outcomes examined.

Specifically, within-child associations between cumulative risk and reading achievement did vary by the level of cumulative risk children were experiencing at Wave 1. For children who were experiencing no or very low risk across all four risk domains at Wave 1, changes in risk were not significantly associated with changes in reading scores. For children who were experiencing high risk in a least one risk domain at Wave 1, a 0.25-unit increase/decrease in cumulative risk were associated with about a 4-point change, or about a third of an average year's growth, in reading achievement. For children who were experiencing high risk in all four risk domains at Wave 1, a 0.25-unit increase/decrease in cumulative risk were associated with about a 14-point change, or more than an average year's growth, in reading achievement.

It should be noted, however, that because the moderator being examined is *initial* level of cumulative risk, these results likely reflect a combination of cumulative risk level and age effects. That is, it is not just that families experiencing higher levels are most affected by changes in risk, but more specifically, that families experiencing higher levels of risk *at this particular stage in their child's development*, are most affected by changes in risk. These findings must then be interpreted in combination with the child age results discussed above, which indicated that associations between cumulative risk and child cognitive/academic outcomes were stronger for children who were 5, 6, and 7 years old at the start of the study (compared to children who were 3 or 4 years old at the start of the study). Together, these results suggest that policies and programs designed to reduce the range of contextual risk factors to which a child is exposed may be most effective for children identified as facing multiple risk factors in their early elementary years. Though the present results do not speak to the question of whether the timing of the changes in risk themselves matters. Additional research is needed to further explore and disentangle the complex interactions between child age, level of risk, and timing of changes in risk.

Lagged Models

While not a primary goal of the present dissertation research, structural equation modeling offered an opportunity not only to check the robustness of the fixed effects regression model findings, but also to explore the possibility that within-child changes in income and/or changes in cumulative risk may have a lagged effect on changes in child outcomes, as suggested by previous research (Thomson, Dearing, & Coley, unpublished).

The results of these additional SEM models indicate that changes in family income were significantly associated with changes in cumulative risk, and that these decreases in risk were, in turn, significantly associated with increases in children's math skills, as well as decreases in both externalizing and internalizing behaviors, five years later. Associations between changes in cumulative risk and child working memory and reading achievement five years later approached significance.

Interestingly, effect sizes for the associations between income and child academic outcomes and for the associations between cumulative risk and child academic outcomes were generally larger in the lagged models than the non-lagged models. However, the opposite was true of children's socioemotional outcomes: effect sizes for the associations between income and child socioemotional outcomes and for the associations between cumulative risk and child socioemotional outcomes were generally larger in the non-lagged models than the lagged models. These findings suggest that the lagged models may be a better fit to the data when considering academic outcomes, and the non-lagged models a better fit when considering socioemotional outcomes. Future research examining associations between income or cumulative risk and children's academic outcomes should keep in mind the possibility of stronger lagged effects.

Implications and Recommendations

A number of key patterns emerge from the results that have important implications for our understanding of how poverty impacts child development, and for the design of effective policies and interventions. First and foremost, the findings of the present study provide empirical evidence that changes in family income are indeed linked to changes in cumulative risk exposure, and that these changes in turn predict changes in child achievement and externalizing behaviors. These findings supports growing evidence that exposure to cumulative contextual risks does help to explain the pernicious effects of poverty on child academic achievement and psychosocial functioning.

From a policy standpoint, these results also crucially highlight that child outcomes are malleable and responsive to improvements in family economic conditions. Moreover, the results point to multiple levers for intervention. Programs designed to reduce any number of poverty-associated risk factors, as well as both cash and non-cash transfers to high-risk families, are likely to be effective in improving child achievement and socio-emotional functioning. Examples of programs to reduce poverty-associated risk factors include programs designed to help poor and low-income families manage overwhelming financial stressors and plan for future budgetary priorities; waivers to move to safer neighborhoods or that could be used to improve safety and living conditions within the home; and the provision of free/accessible mental health, parenting, and conflict resolution support for caregivers and their families. Examples of programs design to boost families' income (or free up limited resources) include the Earned Income Tax Credit, Child Tax Credit, Medicare and Children's Health Insurance Program, food stamps and housing assistance programs, and state or community-based programs or services that provide assistance in a range of ways when a family experiences a loss in income.

In addition, in considering variation in the associations between family income, cumulative risk, and child outcomes, the present study provides robust evidence that the associations between changes in a family's economic circumstances, changes in exposure to stressful circumstances, and changes in child outcomes depend on level of income and child age. The results also suggest the some of the associations between family income, cumulative risk, and child outcomes may vary by race/ethnicity. These findings support Marc Bornstein's (2017) specificity principle, which argues that while some life circumstances or experiences may have broad implications for development, the precise role of such circumstances or experiences depends upon not only the specific circumstances or experiences involved, but also "who experiences and who generates the experience, when in life the experience occurs, how the experience occurs, and the domain of development affected by the experience" (p. 5). In line with this specificity principle, present results thus call attention to critical time periods and populations on which to focus interventions and policies.

Specifically, policies and interventions designed to improve children's academic achievement by boosting families' incomes or reducing their exposure to an array of contextual risks, should target children from families who are experiencing/experienced poverty or high levels of contextual risks/stressors in at least one domain during their child's early years. Importantly, however, the present research also indicates that reductions in contextual risks/stressors are likely to have a positive impact on child achievement throughout the school years, and may even play a particularly important role during adolescence. Additional research is necessary to further disentangle the interrelated questions of which children would benefit most from policies and programs designed to improve their family's circumstances and at what time in child growth those policies and programs may be most effective. Additional research is also needed to further explore alternative pathways that might explain the stronger effects of changes in income for preschool-aged children's achievement, which, in the present study, were not found to be mediated by cumulative risk exposure.

Policies and programs that boost families' incomes or reduce their exposure to the array of contextual risks that often accompany, and are likely caused by poverty, can also expect improvements in children's socioemotional functioning – more specifically, reduced externalizing behaviors. The present study suggests that policies and programs that target African-American children and children from low-income families will have the strongest impact on children's psychosocial outcomes. These results also point to the need for more research on the interaction of race-related stressors and poverty-associated contextual risks, as well as how race-related stressors might be accentuated by factors or contexts that might also change as income changes.

Finally, the results of this dissertation highlight an additional avenue for future research with crucial implications for policy and practice. As research builds that implicates the role that cumulative risk plays in the income-achievement gap, more research is desperately needed on potential protective factors that might buffer children from high levels of stress. There is already some reason to believe that high-quality early care – both inside and outside the home – can help to buffer children from high levels of negative emotional arousal or stress reactivity, facilitate self-regulation, and contribute to later regulatory capacities that can off-set stress (Berry et al., 2014; Loman & Gunnar, 2010). However, further research is needed in this area.

Moreover, in light of the presents findings that reductions in contextual risks/stressors are likely to have a positive impact on child achievement throughout the school years, and may even play a particularly important role during adolescence, research is particularly needed that explores the potential role of peer relationships and school environments in either accentuating or attenuating the effects of cumulative risk on child outcomes. Furthermore, research that highlights the skills and tools that could further protect at-risk children from harmful levels of stress – such as mindfulness and movement-based therapeutic strategies, executive functioning and goal-setting skills, to name just a few – is also desperately needed to facilitate the development of school-based programs that can help children build these tools.

Limitations and Strengths

The nationally representative sample and the wide range of rich, repeated measures contained in the PSID Child Development Supplement is a key strength of the present study. The analyses were nonetheless limited by the relatively small number of data collection time points (3), as well as the relatively long duration of time between waves (5 years). The three time points across ten years provided a window into a large portion of each child's life, a large span of time between waves can often make it harder to detect small changes in growth. Furthermore, with only three waves of data, it was necessary to assume linear growth, while additional waves may have allowed us to posit more flexible models with less restrictive assumptions (Singer & Willet, 2003).

Also, because these analyses were based on a secondary dataset, there are a number of limitations related to measurement of constructs. First, many of the measures (with the exception of the measures related to the physical home environment and children's cognitive and academic outcomes) were based on parent report. While it could be argued that perceptions of hardship and risks may be more important than objective measures when trying to understand the level of stress a family is experiencing, it is worth noting that these perceptions of stress are likely relative to a family's circumstances. For example, a parent's judgment as to whether the neighborhood they are living in is safe is likely made in the context of the range of neighborhoods with which that parent is familiar. In this way, a middle income family's idea of economic strain or a suitable neighborhood for raising children might be different than that of a poor family's. Parents may also acculturate themselves to changes in income, such that their own expectations change as their income changes. Objective measures would have reduced the potential for shared error variance in parent-reported variables (Mayer, 1997).

A second point with respect to measurement is that while principle components factor analyses indicated four domains of risk exposure, individual indicators of risk within a particular domain of risk did not always demonstrate high internal consistency. The importance of these psychometric characteristics, however, was thought to be less critical given that we did not expect nor require, based on theory, that individual risk indicators be correlated, but rather only that accumulating more risk would be more harmful than accumulating less risk (also see Bradley, 2004, for a full discussion of the underlying logic). For example, aggravation in parenting, maternal depression, and intra-family conflict and violence might not necessarily be highly correlated but each represents an important dimension of higher-risk psychological home environments. Moreover, alternative specifications of the threshold-based index of cumulative risk were explored and the findings were surprisingly robust.

Finally, a major limitation of the majority of research investigating the pathways through which family income influences child outcomes has been that they are non-experimental. Such studies are susceptible to omitted variables bias, or the possibility that the estimated “effect” of income is due to a third set of unobserved variables that might predict both family income and child outcomes, and is the “true” underlying cause of the observed differences in children’s outcome that have been found to be associated with differences in family income. The present research is also correlational, and thus non-experimental, in design. However, a strength of the fixed-effects analysis used in the present research is that it is able to control for both observed and unobserved time-invariant variables. There could, of course, still be bias associated with time-varying factors, but overall, “omitted variable bias” is thought to be greatly reduced in fixed-effects models.

Moreover, an additional strength of the present research is the wide range of time-varying controls (changes in number of siblings, partner status, whether other adults are living in the home, head education level, employment status, and government assistance) used to isolate the unique influence of changes in income and cumulative risk on children’s outcome. In this way, the present analyses provide better support for causal argument than models that do not examine within-child change or account for a range of potential time-varying factors associated with changes in income and that influence child development (Dearing, McCartney, & Taylor, 2001; Dearing, McCartney, & Taylor, 2006; Dearing & Taylor, 2007; Duncan et al., 1998). That said, it is clear from some of the results presented here that changes in family income and cumulative risk may indeed be related to a range of variables that are not measured in the present analyses and that likely fluctuate in advance of, along with, or in response to changes in families’ income and circumstances. There are certainly government-, community-, and family-based supports and services that fluctuate as family’s experience increases or decreases in income or risk, as discussed above. It is also possible that other factors that have been identified in cross-sectional research as exogenous predictors of both family income and child cognitive and social outcomes (Blau, 1999), such as parent motivation or self-efficacy, can also vary over time in advance of, along with, or in response to changes in families' income and circumstances.

Correlational analyses, including fixed effects analyses, are also limited in their ability to speak to questions about directionality: for example, whether changes in cumulative risk affect family income, or whether changes in children's outcomes affect cumulative risk, rather than vice versa in each case. A strength of the present research, however, is that it attempts to address just this issue by examining lagged models in which the timing of changes in family income (which reflects family income the year prior to data collection) temporally precedes changes in cumulative risk, which precedes changes in children's outcomes (in the subsequent wave). Significant findings from these lagged models provide additional argument for causality.

A separate, and arguably just as important, question is whether, even if causality could be established, *changes* in income and/or changes in a family's circumstances matter. This question is also critical for developmental theory, policy, and the design of effective interventions. One could even make the case that there is some benefit, even if it comes with additional complexity and messiness, to examining within-family changes in income non-experimentally, as it may more closely reflect how children's development may be influenced by more natural-occurring increases and decreases in family income (including government assistance) and changes in their family circumstances. Such "natural" increases and decreases in income or circumstances may be more likely to influence how parents budget, allocate resources, make decisions about childcare, and think about the future, than the one-time changes or changes of limited duration that are more characteristic of the types of exogenous changes in income (or risk) examined in experimental studies. Studies of naturally-occurring changes in family circumstances may lead to a better understanding of the influence of income and risk in the context of how families actually weigh different types of risks and factors related to decision-making, in a way that is particularly critical for effective interventions with long-lasting and sustainable effects on family circumstances that related to children's wellbeing (Rosenblatt & DeLuca, 2012).

Conclusion

The present study adds to the growing body of research that has highlighted the consequences of stress for children's developing brains, and has further suggested that exposure to a range of contextual stressors may help to explain the harmful effects of poverty on child achievement and psychosocial functioning. Using the Panel Study of Income Dynamics Child Development Supplement's nationally representative sample of 1,384 children aged 3-7 years in Wave 2 and 13-17 years at Wave 3, the results of the present study are broadly consistent with the Cumulative Risk Model, finding significant indirect effects of family income, through cumulative risk, on children's reading and math achievement and externalizing behaviors. More specifically, changes in family income are associated with changes in cumulative risk, which are in turn associated with changes in children's reading and math achievement and externalizing scores. The fixed effects regression estimates imply that for families at the lower end of the income distribution, a $10,000 increase in income was associated with a decrease equivalent to

89% of the average between-child standard deviation in cumulative risk, which is in turn associated with an increase of about 9% of the average between-child standard deviation in reading achievement, 7% of a standard deviation in math achievement, and a decrease of about 8% of a standard deviation in externalizing behaviors.

The results also indicate that within-child associations between family income are stronger for children from families with lower initial incomes (at Wave 1) and younger children. These moderated effects of income, however are not mediated by cumulative risk, suggesting that other pathways, such as those posited by the Parental Investment Model and Family Stress Model, might also play a role in mediating the effects of income on child outcomes for preschool-aged low-income children in particular. Within-child associations between family income and cumulative stress are also stronger for those at with lower initial incomes but do not vary by child age or race. Lastly, within-child associations between cumulative risk and children's socioemotional outcomes are larger for children from families with lower initial incomes and for African-American children, while within-child associations between cumulative risk and children's cognitive/academic outcomes are larger for children who experienced high levels of risk during their early years, but also for older children in the sample. The latter finding, in particular, suggests that while children who a wider array of poverty-associated stressors in their early years may be most at risk for diminished achievement and socioemotional functioning, reductions in contextual risks/stressors are likely to have a positive impact on child achievement throughout the school years, and may even play a particularly important role during adolescence.

These findings have important policy and practice implications. Specifically, the results provide empirical evidence that both risk exposure and, in turn, child outcomes are malleable and responsive to improvement in family economic conditions. They also call attention to critical times periods and populations on which to focus interventions and policies. Moroever, the use of fixed-effects analyses to address common problems associated with unobserved time-invariant influences is promising from both a cause probing and policy making standpoint. While caution is always warranted in drawing implications from correlational designs, the present analyses also controlled for a wide range time-varying covariates, were found to be robust to a variety of alternative specifications, and were replicated in lagged models, further increasing confidence in the estimates found in the present research.

References

Adam, E., Heissel, J., Zeiders, K., Richeson, J., Brodish, A., Ross, E., … Eccles, J. (2015). Developmental histories of perceived racial discrimination and diurnal cortisol profiles in adulthood: A 20-year prospective study. *Psychoneuroendocrinology 62*, 279-291.

Ainsworth, J. W. (2002). Why does it take a village? The mediation of neighborhood effects on educational achievement. *Social Forces, 81*, 117-152.

Allison, P. D. (2009). *Fixed effects regression models*. Thousand Oaks, CA: Sage publications.

American Psychological Association (2016). *Stress in America: The impact of discrimination.* Stress in America Survey.

Arnsten, A. F. (2009). Stress signalling pathways that impair prefrontal cortex structure and function. *Nature Reviews Neuroscience*, *10*(6), 410-422.

Attar, B. K., Guerra, N. G., & Tolan, P. H. (1994). Neighborhood disadvantage, stressful life events and adjustments in urban elementary-school children. *Journal of Clinical Child Psychology*, *23*(4), 391-400.

Bailey, M. J., & Dynarski, S. M. (2011). *Gains and gaps: Changing inequality in US college entry and completion* (No. w17633). National Bureau of Economic Research.

Becker, G. S., & Tomes, N. (1994). Human capital and the rise and fall of families. In *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education (*3rd Edition; pp. 257-298). Chicago: The University of Chicago Press.

Berry, D., Blair, C., Ursache, A., Willoughby, M., Garrett-Peters, P., Vernon-Feagans, L., ... & Granger, D. A. (2014). Child care and cortisol across early childhood: Context matters. *Developmental Psychology*, *50*(2), 514-525.

Blair, C., Berry, D., Mills-Koonce, R., Granger, D., & FLP Investigators. (2013). Cumulative effects of early poverty on cortisol in young children: Moderation by autonomic nervous system activity. *Psychoneuroendocrinology*, *38*(11), 2666-2675.

Blair, C., Granger, D. A., Kivlighan, K. T., Mills-Koonce, R., Willoughby, M., Greenberg, M. T., ... & Fortunato, C. K. (2008). Maternal and child contributions to cortisol response to emotional arousal in young children from low-income, rural communities. *Developmental Psychology*, *44*(4), 1095-1109.

Blair, C., Raver, C. C., Granger, D., Mills-Koonce, R., & Hibel, L. (2011). Allostasis and allostatic load in the context of poverty in early childhood. *Development and Psychopathology*, *23*(3), 845-857.

Bradley, R. H., & Corwyn, R. F. (2002). Socioeconomic status and child development. *Annual Review of Psychology*, *53*(1), 371-399.

Briggs‐Gowan, M. J., Ford, J. D., Fraleigh, L., McCarthy, K., & Carter, A. S. (2010). Prevalence of exposure to potentially traumatic events in a healthy birth cohort of very young children in the northeastern United States. *Journal of Traumatic Stress*, *23*(6), 725-733.

Bronfenbrenner, U. (1986). Ecology of the family as a context for human development: Research perspectives. *Developmental Psychology*, *22*(6), 723.

Bronfenbrenner, U., & Morris, P. A. (2006). The bioecological model of human development. *Handbook of Child Psychology*. Hoboken, NJ: John Wiley & Sons, Inc.

Brooks-Gunn, J., & Duncan, G. J. (1997). The effects of poverty on children. *The future of children*, 7(2), 55-71.

Brooks-Gunn, J., Duncan, G. J., & Maritato, N. (1997). Poor families, poor outcomes: The well-being of children and youth. In G. J. Duncan & J. Brooks-Gunn (Eds.), *Consequences of growing up poor* (pp. 1-17). New York, NY: Russell Sage Foundation.

Burchinal, M., Nelson, L., Carlson, M., & Brooks-Gunn, J. (2008). Neighborhood characteristics, and child care type and quality. *Early Education and Development*, *19*(5), 702-725.

Burchinal, M. R., Roberts, J. E., Hooper, S., & Zeisel, S. A. (2000). Cumulative risk and early cognitive development: a comparison of statistical risk models. *Developmental Psychology*, *36*(6), 793.

Burchinal, M., Vernon-Feagans, L., Cox, M., & Key Family Life Project Investigators. (2008). Cumulative social risk, parenting, and infant development in rural low-income communities. *Parenting: Science and Practice*, *8*(1), 41-69.

Chen, E., Cohen, S., & Miller, G. E. (2010). How low socioeconomic status affects 2-year hormonal trajectories in children. *Psychological Science*, *21*(1), 31-37.

Chetty, R., & Hendren, N. (2015). The impacts of neighborhoods on intergenerational mobility: Childhood exposure effects and county-level estimates. Harvard University and NBER.

Chetty, R., Hendren, N., & Katz, L. F. (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *The American Economic Review*, *106*(4), 855-902.

Chiao, J. Y., & Blizinsky, K. D. (2013). Population disparities in mental health: Insights from cultural neuroscience. *American Journal of Public Health*, *103*(1), S122-S132.

Coleman, J. (1990). *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.

Conger, R. D., & Conger, K. J. (2002). Resilience in Midwestern families: Selected findings from the first decade of a prospective, longitudinal study. *Journal of Marriage and Family*, *64*(2), 361-373.

Conger, R. D., Conger, K. J., & Elder, G. H. (1997). Family economic hardship and adolescent adjustment: Mediating and moderating processes. *Consequences of growing up poor*, *34*.

Conger, R. D., Conger, K. J., & Martin, M. J. (2010). Socioeconomic status, family processes, and individual development. *Journal of Marriage and Family*, *72*(3), 685-704.

Conger, R. D., & Donnellan, M. B. (2007). An interactionist perspective on the socioeconomic context of human development. *Annual Review of Psychology, 58*, 175-199.

Conger, R. D., Ge, X., Elder, G. H., Lorenz, F. O., & Simons, R. L. (1994). Economic stress, coercive family process, and developmental problems of adolescents. *Child Development*, *65*(2), 541-561.

Conger, R. D., Wallace, L. E., Sun, Y., Simons, R. L., McLoyd, V. C., & Brody, G. H. (2002). Economic pressure in African American families: a replication and extension of the family stress model. *Developmental Psychology*, *38*(2), 179-193.

Congressional Budget Office. (2014). *Trends in the distribution of household income between 1979 and 2011*. Pub. No. 4031. Retrieved December 4, 2015, from https://www.cbo.gov/publication/42729?index=12485

Conway, A., Kane, M., Bunting, M., Hambrick, Z., Wilhelm, O., & Engle, R. (2005). Working memory span tasks: A methodological review and user's guide. *Psychonomic Bulletin and Review, 12* (5), 769-786.

Cooley-Quille, M., Boyd, R. C., Frantz, E., & Walsh, J. (2001). Emotional and behavioral impact of exposure to community violence in inner-city adolescents. *Journal of Clinical Child Psychology*, *30*(2), 199-206.

Corcoran, M. E., & Chaudry, A. (1997). The dynamics of childhood poverty. *The Future of Children*, *7*(2), 40-54.

Cradock, A. L., Kawachi, I., Colditz, G. A., Hannon, C., Melly, S. J., Wiecha, J. L., & Gortmaker, S. L. (2005). Playground safety and access in Boston neighborhoods. *American journal of preventive medicine*, *28*(4), 357-363.

Criss, M. M., Pettit, G. S., Bates, J. E., Dodge, K. A., & Lapp, A. L. (2002). Family adversity, positive peer relationships, and children’s externalizing behavior: A longitudinal perspective on risk and resilience. *Child development*, *73*(4), 1220-1237.

Cummings, E. M., Zahn-Waxler, C., & Radke-Yarrow, M. (1981). Young children's responses to expressions of anger and affection by others in the family. *Child Development*, 1274-1282.

Cunha, F., & Heckman, J. (2007). *The technology of skill formation* (Working Paper #w12840). National Bureau of Economic Research.

Cunha, F., & Heckman, J. J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources*, *43*(4), 738-782.

Dadds, M. R., & Powell, M. B. (1991). The relationship of interparental conflict and global marital adjustment to aggression, anxiety, and immaturity in aggressive and nonclinic children. *Journal of Abnormal Child Psychology*, *19*(5), 553-567.

Dahl, T., Ceballo, R., & Huerta, M. (2010). In the eye of the beholder: Mothers' perceptions of poor neighborhoods as places to raise children. *Journal of Community Psychology*, *38*(4), 419-434.

Dearing, E. (2008). Psychological costs of growing up poor. *Annals of the New York Academy of Sciences*, *1136*(1), 324-332.

Dearing, E., McCartney, K., & Taylor, B. A. (2001). Change in family income‐to‐needs matters more for children with less. *Child Development*, *72*(6), 1779-1793.

Dearing, E., McCartney, K., & Taylor, B. A. (2006). Within-child associations between family income and externalizing and internalizing problems. *Developmental Psychology*, *42*(2), 237-252.

Dearing, E., & Taylor, B. A. (2007). Home improvements: Within-family associations between income and the quality of children's home environments. *Journal of Applied Developmental Psychology*, *28*(5), 427-444.

Deater–Deckard, K., Dodge, K. A., Bates, J. E., & Pettit, G. S. (1998). Multiple risk factors in the development of externalizing behavior problems: Group and individual differences. *Development and psychopathology*, *10*(03), 469-493.

de Kloet, E. R., Oitzl, M. S., & Joëls, M. (1999). Stress and cognition: are corticosteroids good or bad guys? *Trends in Neurosciences*, *22*(10), 422-426.

Duncan, G. J., & Brooks-Gunn, J. (1997). Income effects across the life span: Integration and interpretation. In G. J. Duncan & J. Brooks-Gunn (Eds.), *Consequences of growing up poor* (pp. 596-610). New York: Russell Sage Foundation.

Duncan, G. J., & Brooks‐Gunn, J. (2000). Family poverty, welfare reform, and child development. *Child Development*, *71*(1), 188-196.

Duncan, G. J., Ziol‐Guest, K. M., & Kalil, A. (2010). Early‐childhood poverty and adult attainment, behavior, and health. *Child Development*, *81*(1), 306-325.

Duncan, G. J., Ludwig, J., & Magnuson, K. (2010). Child development. Working Paper for NBER conference, *Targeting investments in children: Fighting poverty when resources are limited*. Retrieved from sites.uci.edu/gduncan/files/2013/06/Duncan-Ludwig-Magnuson-NBER-chapter.pdf

Duncan, G. J., & Magnuson, K. (2011). The nature and impact of early achievement skills, attention skills, and behavior problems. In R. Murnane & G. Duncan

(Eds.), *Whither opportunity? Rising inequality and the uncertain life chances of low-income children* (pp. 47-70). New York, NY: Russell Sage Foundation.

Duncan, G., & Magnuson, K. (2013). The importance of poverty early in childhood. *Policy Quarterly*, *9*(2), 12-17.

Duncan, G. J., Magnuson, K. A., & Ludwig, J. (2004). The endogeneity problem in developmental studies. *Research in Human Development*, *1*(1-2), 59-80.

Dynan, K. E., Elmendorf, D. W., & Sichel, D. E. (2007). *The evolution of household income volatility*. FEDS Working Paper #2007-61. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1051141

Eamon, M. K. (2002). Poverty, parenting, peer, and neighborhood influences on young adolescent antisocial behavior. *Journal of Social Service Research*, *28*(1), 1-23.

Ellen, I. G., Mijanovich, T., & Dillman, K. N. (2001). Neighborhood effects on health: exploring the links and assessing the evidence. *Journal of Urban Affairs*, *23*(3-4), 391-408.

Enders, C. K. (2010). *Applied missing data analysis*. Guilford Press.

Erickson, K., Drevets, W., & Schulkin, J. (2003). Glucocorticoid regulation of diverse cognitive functions in normal and pathological emotional states. *Neuroscience & Biobehavioral Reviews*, *27*(3), 233-246.

Estrada-Martínez, L. M., Caldwell, C. H., Bauermeister, J. A., & Zimmerman, M. A. (2012). Stressors in multiple life-domains and the risk for externalizing and internalizing behaviors among African Americans during emerging adulthood. *Journal of Youth and Adolescence*, *41*(12), 1600-1612.

Evans, G. W. (2003). A multimethodological analysis of cumulative risk and allostatic load among rural children. *Developmental psychology*, *39*(5), 924.

Evans, G. W. (2004). The environment of childhood poverty. *American Psychologist*, *59*(2), 77-92.

Evans, G. W. (2006). Child development and the physical environment. *Annual Review of Psychology*, *57*, 423-451.

Evans, G. W., & English, K. (2002). The environment of poverty: Multiple stressor exposure, psychophysiological stress, and socioemotional adjustment. *Child Development*, *73*(4), 1238-1248.

Evans, G. W. & Kim, P. (2013). Childhood Poverty, Chronic Stress, Self-Regulation, and Coping. *Child Development Perspectives, 7*, 43–48.

Evans, G. W., Li, D., & Whipple, S. S. (2013). Cumulative risk and child development. *Psychological Bulletin*, *139*(6), 1342.

Evans, G. W., Rhee, E., Forbes, C., Allen, K. M., & Lepore, S. J. (2000). The meaning and efficacy of social withdrawal as a strategy for coping with chronic residential crowding. *Journal of Environmental Psychology*, *20*(4), 335-342.

Evans, G. W., & Schamberg, M. A. (2009). Childhood poverty, chronic stress, and adult working memory. *Proceedings of the National Academy of Sciences*, *106*(16), 6545-6549.

Evans, G. W., & Saegert, S. (2000). Residential crowding in the context of inner city poverty. In S. Wapner (Ed.), *Theoretical perspectives in environment-behavior research* (pp. 247-267). New York: Springer US.

Farkas, G. (2011). Middle and high school skills, behaviors, attitudes, and curriculum enrollment, and their consequences. In R. Murnane & G. Duncan (Eds.), *Whither opportunity? Rising inequality and the uncertain life chances of low-income children* (pp. 71-90). New York, NY: Russell Sage Foundation.

Ferguson, K. T., Cassells, R. C., MacAllister, J. W., & Evans, G. W. (2013). The physical environment and child development: An international review. *International Journal of Psychology*, *48*(4), 437-468.

Foster, E. M. (2010). Causal inference and developmental psychology. *Developmental psychology*, *46*(6), 1454.

Fuller, B., Kagan, S. L., Caspary, G. L., & Gauthier, C. A. (2002). Welfare reform and child care options for low-income families. *The Future of Children*, 97-119.

García, E. (2015). Inequalities at the starting gate: Cognitive and noncogntive skills gaps etween 2010-2011 kindergarten classmates. Economic Policy Institute.

Ge, X., Conger, R. D., & Elder Jr, G. H. (2001). Pubertal transition, stressful life events, and the emergence of gender differences in adolescent depressive symptoms. *Developmental psychology*, *37*(3), 404.

Gershoff, E.T., Aber, J.L., Raver, C.C., & Lennon, M.C. (2007). Income is not enough: Incorporating material hardship into models of income associations with parenting and child development. *Child Development, 78*, 70–95

Granger, D. A., Stansbury, K., & Henker, B. (1994). Preschoolers' behavioral and neuroendocrine responses to social challenge. *Merrill-Palmer Quarterly, 40*(2), 190-211.

Granger, D. A., Weisz, J. R., McCracken, J. T., Ikeda, S. C., & Douglas, P. (1996). Reciprocal Influences among Adrenocortical Activation, Psychosocial Processes, and the Behavioral Adjustment of Clinic‐Referred Children. *Child Development*, *67*(6), 3250-3262.

Grant, K. E., Compas, B. E., Stuhlmacher, A. F., Thurm, A. E., McMa- hon, S. D., & Halpert, J. A. (2003). Stressors and child and adolescent psychopathology: Moving from markers to mechanisms of risk. *Psychological Bulletin, 129*, 447–466.

Grant, K. E., McCormick, A., Poindexter, L., Simpkins, T., Janda, C. M., Thomas, K. J., ... & Taylor, J. (2005). Exposure to violence and parenting as mediators between poverty and psychological symptoms in urban African American adolescents. *Journal of Adolescence*, *28*(4), 507-521.

Grant, K., Poindexter, L., Davis, T., Cho, M. H., McCormick, A., & Smith, K. (2000). Economic stress and psychological distress among urban African American adolescents: The mediating role of parents. *Journal of Prevention & Intervention in the Community*, *20*(1-2), 25-36.

Gunnar, M. R., & Donzella, B. (2002). Social regulation of the cortisol levels in early human development. *Psychoneuroendocrinology*, *27*(1), 199-220.

Gunnar, M., & Quevedo, K. (2007). The neurobiology of stress and development. *Annual Review of Psychology*, *58*, 145-173.

Gunnar, M. R., & Vazquez, D. M. (2001). Low cortisol and a flattening of expected daytime rhythm: Potential indices of risk in human development. *Development and psychopathology*, *13*(03), 515-538.

Gutman, L. M., Sameroff, A. J., & Cole, R. (2003). Academic growth curve trajectories from 1st grade to 12th grade: Effects of multiple social risk factors and preschool child factors. *Developmental Psychology*, *39*(4), 777.

Hackman, D. A., Gallop, R., Evans, G. W., & Farah, M. J. (2015). Socioeconomic status and executive function: Developmental trajectories and mediation. *Developmental Science*, *18*(5), 686-702.

Halpern, L. F. (2004). The relations of coping and family environment to preschoolers' problem behavior. *Journal of Applied Developmental Psychology*, *25*(4), 399-421.

Heckman, J. J. (2008). Schools, skills, and synapses. *Economic Inquiry, 46*(3), 289-324.

Heckman, J. J., & Kautz, T. (2012). Hard evidence on soft skills. *Labour Economics*, *19*(4), 451-464.

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., & Yavitz, A. (2010). The rate of return to the High Scope Perry Preschool Program. *Journal of Public Economics*, *94*(1), 114-128.

Hicken, M. T., Lee, H., Morenoff, J., House, J. S., & Williams, D. R. (2014). Racial/ethnic disparities in hypertension prevalence: reconsidering the role of chronic stress. *American Journal of Public Health*, *104*(1), 117-123.

Hooper, S. R., Burchinal, M. R., Roberts, J. E., Zeisel, S., & Neebe, E. C. (1998). Social and family risk factors for infant development at one year: An application of the cumulative risk model. *Journal of Applied Developmental Psychology*, *19*(1), 85-96.

Iceland, J., & Bauman, K. J. (2007). Income poverty and material hardship: how strong is the association?. *The Journal of Socio-Economics*, *36*(3), 376-396.

Israel, B. A., Schulz, A. J., Estrada-Martinez, L., Zenk, S. N., Viruell-Fuentes, E., Villarruel, A. M., & Stokes, C. (2006). Engaging urban residents in assessing neighborhood environments and their implications for health. *Journal of Urban Health*, *83*(3), 523-539.

Jennings, J. L., & DiPrete, T. A. (2010). Teacher effects on social and behavioral skills in early elementary school. *Sociology of Education*, *83*(2), 135-159.

Joëls, M., & Baram, T. Z. (2009). The neuro-symphony of stress. *Nature Reviews Neuroscience*, *10*(6), 459-466.

Kalil, A., & Dunifon, R. (2007). Maternal work and welfare use and child well-being: Evidence from 6 years of data from the Women's Employment Study. *Children and Youth Services Review*, *29*(6), 742-761.

Karb, R. A., Elliott, M. R., Dowd, J. B., & Morenoff, J. D. (2012). Neighborhood-level stressors, social support, and diurnal patterns of cortisol: The Chicago Community Adult Health Study. *Social Science & Medicine*, *75*(6), 1038-1047.

Kliewer, W., Lepore, S. J., Oskin, D., & Johnson, P. D. (1998). The role of social and cognitive processes in children's adjustment to community violence. *Journal of consulting and clinical psychology*, *66*(1), 199.

Kujala, T., & Brattico, E. (2009). Detrimental noise effects on brain's speech functions. *Biological Psychology*, *81*(3), 135-143.

Lee, M. Y. (2001). Marital violence: Impact on children's emotional experiences, emotional regulation and behaviors in a post-divorce/separation situation. *Child and Adolescent Social Work Journal*, *18*(2), 137-163.

Leininger, J. L., & Kalil, A. (2014). Economic strain and children's behavior in the aftermath of the Great Recession. *Journal of Marriage and Family*, *76*(5), 998-1010.

Lengua, L. J., Honorado, E., & Bush, N. R. (2007). Contextual risk and parenting as predictors of effortful control and social competence in preschool children. *Journal of Applied Developmental Psychology*, *28*(1), 40-55.

Leventhal, T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin*, *126*(2), 309.

Leventhal, T., & Newman, S. (2010). Housing and child development. *Children and Youth Services Review*, *32*(9), 1165-1174.

Linver, M.R., Brooks-Gunn, J., & Kohen, D. (2002). Family processes as pathways from income to young children's development. *Developmental Psychology, 38*, 719–734.

Lupien, S. J., King, S., Meaney, M. J., & McEwen, B. S. (2001). Can poverty get under your skin? Basal cortisol levels and cognitive function in children from low and high socioeconomic status. *Development and Psychopathology*, *13*(3), 653-676.

Lupien, S. J., McEwen, B. S., Gunnar, M. R., & Heim, C. (2009). Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature Reviews Neuroscience*, *10*(6), 434-445.

Lynch, M. (2003). Consequences of children's exposure to community violence. *Clinical child and family psychology review*, *6*(4), 265-274.

Magnuson, K. A., & Votruba-Drzal, E. (2008). *Enduring influences of childhood poverty*. University of Wisconsin-Madison, Institute for Research on Poverty.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013). Poverty impedes cognitive function. *science*, *341*(6149), 976-980.

MacKinnon, D. P. (2008). *Introduction to statistical mediation analysis*. New York: Taylor & Francis Group, LLC.

Margolin, G., & Gordis, E. B. (2004). Children's exposure to violence in the family and community. *Current Directions in Psychological Science*, *13*(4), 152-155.

Martin, M. J., Conger, R. D., Schofield, T. J., Dogan, S. J., Widaman, K. F., Donnellan, M. B., & Neppl, T. K. (2010). Evaluation of the interactionist model of socioeconomic status and problem behavior: A developmental cascade across generations. *Development and psychopathology*, *22*(03), 695-713.

Masten, A. S., & Coatsworth, J. D. (1998). The development of competence in favorable and unfavorable environments: Lessons from research on successful children. *American psychologist*, *53*(2), 205.

McCartney, K., Bub, K. L., & Burchinal, M. R. (2006). VI. Selection, detection, and reflection. *Monographs of the Society for Research in Child Development*, *71*(3), 105-126.

McDonald, M. A., Sigman, M., Espinosa, M. P., & Neumann, C. G. (1994). Impact of a temporary food shortage on children and their mothers. *Child Development*, *65*(2), 404-415.

McEwen, B. S. (2004). Protection and damage from acute and chronic stress: Allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders. *Annals of the New York Academy of Sciences*, *1032*(1), 1-7.

McEwen, B. S. (2006). Protective and damaging effects of stress mediators: Central role of the brain. *Dialogues in Clinical Neuroscience*, *8*(4), 367.

McLanahan, S. (2009). Fragile families and the reproduction of poverty. *The Annals of the American Academy of Political and Social Science*, *621*(1), 111-131.

McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist*, *53*(2), 185.

Meaney, M. J., & Szyf, M. (2005). Maternal care as a model for experience-dependent chromatin plasticity?. *Trends in Neurosciences*, *28*(9), 456-463.

Mistry, R. S., Vandewater, E. A., Huston, A. C., & McLoyd, V. C. (2002). Economic wellbeing and children's social adjustment: The role of family process in an ethnically diverse low‐income sample. *Child Development*, *73*(3), 935-951.

Mistry, R. S., Benner, A. D., Biesanz, J. C., Clark, S. L., & Howes, C. (2010). Family and social risk, and parental investments during the early childhood years as predictors of low-income children's school readiness outcomes. *Early Childhood Research Quarterly*, *25*(4), 432-449.

Morris, P., Duncan, G., & Rodrigues, C. (2006). Does money really matter? Estimating impacts of family income on young children’s achievement with data from random-assignment experiments. *Unpublished manuscript, MDRC, New York, NY*.

Newland, R. P., Crnic, K. A., Cox, M. J., & Mills-Koonce, W. R. (2013). The family model stress and maternal psychological symptoms: Mediated pathways from economic hardship to parenting. *Journal of Family Psychology*, *27*(1), 96.

Parke, R. D., Coltrane, S., Duffy, S., Buriel, R., Dennis, J., Powers, J., ... & Widaman, K. F. (2004). Economic stress, parenting, and child adjustment in Mexican American and European American families. *Child Development*, *75*(6), 1632-1656.

Peck, S., Sameroff, A., Ramey, S., & Ramey, C. (1999). Transition into school: Ecological risks for adaptation and achievement in a national sample. In *Biennial Meeting of the Society for Research and Development, Albuquerque, NM*.

Rauh, V. A., Parker, F. L., Garfinkel, R. S., Perry, J., & Andrews, H. F. (2003). Biological, social, and community influences on third‐grade reading levels of minority Head Start children: A multilevel approach. *Journal of Community Psychology*, *31*(3), 255-278.

Raver, C. C., Gershoff, E. T., & Aber, J. L. (2007). Testing equivalence of mediating models of income, parenting, and school readiness for White, Black, and Hispanic children in a national sample. *Child Development*, *78*(1), 96-115.

Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. In R. Murnane & G. Duncan (Eds.), *Whither opportunity? Rising inequality and the uncertain life chances of low-income children* (pp. 91-116). New York, NY: Russell Sage Foundation.

Reardon, S. F., Fox, L., & Townsend, J. (2015). Neighborhood income composition by household race and income, 1990–2009. *The Annals of the American Academy of Political and Social Science*, *660*(1), 78-97.

Reardon, S. F., & Portilla, X. A. (2016). Recent trends in income, racial, and ethnic school readiness gaps at kindergarten entry. CEPA Working Paper No. 15-02. Retrieved from Stanford Center for Education Policy Analysis: http://cepa.stanford.edu/wp15-02

Repetti, R. L., Taylor, S. E., & Seeman, T. E. (2002). Risky families: family social environments and the mental and physical health of offspring. *Psychological bulletin*, *128*(2), 330-366.

Repetti, R., Wang, S. W., & Saxbe, D. (2009). Bringing It All Back Home How Outside Stressors Shape Families' Everyday Lives. *Current Directions in Psychological Science*, *18*(2), 106-111.

Richters, J. E., & Martinez, P. (1993). Children as victims of and witnesses to violence in a Washington, DC neighborhood. In L. A. Leavitt & N. A. Fox (Eds.), *The psychological effects of war and violence on children*. Psychology Press. Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc.

Rosenblatt, P., & DeLuca, S. (2012). “We don't live outside, we live in here”: Neighborhood and residential mobility decisions among low‐income families. *City & Community*, *11*(3), 254-284.

Rutter, M. (1989). Isle of Wight revisited: Twenty-five years of child psychiatric epidemiology. *Journal of the American Academy of Child & Adolescent Psychiatry*, *28*(5), 633-653.

Salkind, N. J., & Haskins, R. (1982). Negative income tax: The impact on children from low-income families. *Journal of Family Issues*, *3*(2), 165-180.

Sameroff, A. J. (2000). Developmental systems and psychopathology. *Development and psychopathology*, *12*(03), 297-312.

Sameroff, A. J., Bartko, W. T., Baldwin, A., Baldwin, C., & Seifer, R. (1998). Family and social influences on the development of child competence. In M. Lewis, & C. Feiring, *Families, risk, and competence*. New York: Routledge.

Sameroff, A., Gutman, L. M., & Peck, S. C. (2003). Adaptation among youth facing multiple risks: Prospective research findings. In S. S. Luthar (Ed.), *Resilience and vulnerability: Adaptation in the context of childhood adversities* (pp. 364-391). Cambridge: Cambridge University Press.

Sameroff, A. J., & Seifer, R. (1995). Accumulation of environmental risk and child mental health. *Children of poverty: Research, health, and policy issues*, *23*, 233-258.

Sameroff, A. J., Seifer, R., Baldwin, A., & Baldwin, C. (1993). Stability of intelligence from preschool to adolescence: The influence of social and family risk factors. *Child Development*, *64*(1), 80-97.

Sameroff, A. J., Seifer, R., Barocas, R., Zax, M., & Greenspan, S. (1987). Intelligence quotient scores of 4-year-old children: Social-environmental risk factors. *Pediatrics*, *79*(3), 343-350.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "neighborhood effects": Social processes and new directions in research. *Annual Review of Sociology, 28*, 443-478.

Sapolsky, R. M. (1999). Glucocorticoids, stress, and their adverse neurological effects: relevance to aging. *Experimental Gerontology*, *34*(6), 721-732.

Sapolsky, R. M. (2003). Stress and plasticity in the limbic system. *Neurochemical Research*, *28*(11), 1735-1742.

Sapolsky, R. M. (2004). *Why zebras don't get ulcers: The acclaimed guide to stress, stress-related diseases, and coping-now revised and updated*. Macmillan.

Sawyer, P. J., Major, B., Casad, B. J., Townsend, S. S., & Mendes, W. B. (2012). Discrimination and the stress response: psychological and physiological consequences of anticipating prejudice in interethnic interactions. *American Journal of Public Health*, *102*(5), 1020-1026.

Schapkin, S. A., Falkenstein, M., Marks, A., & Griefahn, B. (2006). Executive brain functions after exposure to nocturnal traffic noise: effects of task difficulty and sleep quality. *European Journal of Applied Physiology*, *96*(6), 693-702.

Schwab-Stone, M., Chen, C., Greenberger, E., Silver, D., Lichtman, J., & Voyce, C. (1999). No safe haven II: The effects of violence exposure on urban youth. *Journal of the American Academy of Child & Adolescent Psychiatry*, *38*(4), 359-367.

Sharkey, P., & Faber, J. W. (2014). Where, when, why, and for whom do residential contexts matter? Moving away from the dichotomous understanding of neighborhood effects. *Annual Review of Sociology*, *40*, 559-579.

Phillips, D. A., & Shonkoff, J. P. (Eds.). (2000). *From neurons to neighborhoods: The science of early childhood development*. National Academies Press.

Smith, J. R., Brooks-Gunn, J., & Klebanov, P. K. (1997). The consequences of living in poverty for young children's cognitive and verbal ability and early school achievement. In G. J. Duncan & J. Brooks-Gunn (Eds.), *Consequences of growing* *up poor* (pp. 132–189). New York: Russell Sage Foundation.

Smith, J. R., Brooks‐Gunn, J., Kohen, D., & McCarton, C. (2001). Transitions on and off AFDC: Implications for parenting and children's cognitive development. *Child Development*, *72*(5), 1512-1533.

StataCorp. (2015). *Stata Statistical Software: Release 14.* College Station, TC: StataCorp LP.

Sroufe, L. A., Egeland, B., Carlson, E. A., & Collins, W. A. (2005). *The development of the person*. New York: Guilford.

Ström, S. (2003). Unemployment and families: A review of research. *Social Service Review*, *77*(3), 399-430.

Suor, J. H., Sturge‐Apple, M. L., Davies, P. T., Cicchetti, D., & Manning, L. G. (2015). Tracing differential pathways of risk: Associations among family adversity, cortisol, and cognitive functioning in childhood. *Child Development*, *86*(4), 1142-1158.

Thelen, E, & Smith, L. B. (2006). Dynamic systems theories. In W. Damon & R. M. Lerner (Eds.), *Theoretical models of human development: Vol. 1. Handbook of child psychology. 6th ed*. New York, Wiley.

Thompson, R. A., Flood, M. F., & Goodvin, R. (2006). Social support and developmental psychopathology. *Developmental psychopathology*, *3*, 1-37.

Ulrich-Lai, Y. M., & Herman, J. P. (2009). Neural regulation of endocrine and autonomic stress responses. *Nature Reviews Neuroscience*, *10*(6), 397-409.

Vernon-Feagans, L., Garrett-Peters, P., De Marco, A., & Bratsch-Hines, M. (2012). Children living in rural poverty: The role of chaos in early development. In V.

Maholmes & R. B. Kind (Eds.), *The Oxford handbook of poverty and child development* (pp. 448-466). New York: Oxford University Press.

Viner, R. M., Ozer, E. M., Denny, S., Marmot, M., Resnick, M., Fatusi, A., & Currie, C. (2012). Adolescence and the social determinants of health. *The lancet*, *379*(9826), 1641-1652.

Votruba‐Drzal, E., Coley, R. L., & Chase‐Lansdale, P. L. (2004). Childcare and low‐income children's development: Direct and moderated effects. *Child Development*, *75*(1), 296-312.

Wadsworth, M. E., Raviv, T., Reinhard, C., Wolff, B., Santiago, C. D., & Einhorn, L. (2008). An indirect effects model of the association between poverty and child functioning: The role of children's poverty-related stress. *Journal of Loss and Trauma*, *13*(2-3), 156-185.

Wadsworth, M. E., & Santiago, C. D. (2008). Risk and resiliency processes in ethnically diverse families in poverty. *Journal of Family Psychology*, *22*(3), 399.

Wagmiller Jr, R. L., Lennon, M. C., Kuang, L., Alberti, P. M., & Aber, J. L. (2006). The dynamics of economic disadvantage and children's life chances. *American Sociological Review*, *71*(5), 847-866.

Yeung, W.J., Linver, M.R., & Brooks-Gunn, J. (2002). How money matters for young children’s development: Parental investment and family processes. *Child Development, 73*, 1861–1879.

Zill, N. (1990). Behavior problems based on parent report. Washington, DC: Child Trends. Retrieved from: http://www.childtrends.org/Files/Child_Trends-1990_11_01_ES_BehaviorProb.pdf

Appendix A: Factor Analysis Results

Table A.1. Rotated Factor Loadings and Unique Variances for Individual Indicators of Cumulative Risk Exposure

Variable Name/Description	**Factor 1** (Physical Home Environment)	**Factor 2** (Psychological Home Environment)	**Factor 3** (Neighborhood Risk)	**Uniqueness**
Economic Strain	0.16	0.49	0.22	**0.68**
Neighborhood is not a good place to raise kids	0.14	-0.06	**0.81**	0.32
Neighborhood is not safe	0.12	0.25	**0.64**	0.51
Home is structurally unsafe, toxins present	**0.49**	0.30	0.24	0.61
Home is not clean	**0.86**	0.01	0.10	0.25
Home is cluttered	**0.82**	0.00	0.10	0.32
Home is monotonous	**0.70**	0.15	0.16	0.46
Family argues a lot, sometimes hits or throws things	0.01	**0.53**	-0.04	0.50
Aggravation in parenting, parenting stress	0.29	**0.59**	0.09	0.53
Maternal depression	0.06	**0.72**	0.07	0.48

Appendix B: Description of Variables

Primary Independent Variable	
Family Income	Total pretax income of all family members living in the household, as reported annually by the head of household in the main PSID family questionnaire for the year prior to the data collection time point. Because the PSID bottom-coded family income at $1 prior to 1994, all waves will be bottom-coded for consistency. Given past evidence of nonlinear income effects, our primary models are based on a natural log transformation of our family income measure.
Mediator Variables	
Cumulative Risk Exposure	Based on both theoretical and empirical considerations, a child's exposure to cumulative poverty-associated contextual risk will be measured by means of a composite index across four domains of risk: economic strain, neighborhood risk, physical home environment, and psychological home environment. Each distinct context of risk is itself composed of multiple indicators that have been dichotomized such that families received a score of 1 if they met or exceeded the risk threshold on that particular item and a score of 0 if they fell below it. (See the proposal narrative for examples of the individual indicators that comprised each of the four domains of risk.)
Child Outcome Variables	
Child Working Memory	Wechsler Digit Span - **Digits Backward** subtest, in which a child listens to a sequence of numbers and repeats them back in reverse order, is used to assess working memory (Wechsler, 1974)
Reading Achievement	Woodcock Johnson Achievement Test **Letter-Word** subtest assesses a student's vocabulary (Woodcock & Johnson, 1989). W scores will be used to allow for comparison of changes in scores and growth across multiple timepoints on a single common scale.
Math Achievement	Woodcock Johnson Achievement Test **Applied Problems** subtest assesses a student's ability to analyze and solve math problems (Woodcock & Johnson, 1989). W scores will be used to allow for comparison of changes in scores and growth across multiple timepoints on a single common scale.
Externalizing Behaviors	A subscale of the Behavior Problem Index (Peterson & Zill, 1986) that measures externalizing and aggressive behavior and is based on parent-report of whether a set of 16 behaviors (e.g., has sudden changes in mood, is restless or overly active, has a very strong temper) is often, sometimes, or never true of their child.
Internalizing Behaviors	A subscale of the Behavior Problem Index (Peterson & Zill, 1986) that measures internalizing, withdrawn, or sad behavior and is based on parent-report of whether a set of 13 behaviors (e.g., is withdrawn, has difficulty getting his/her mind off certain thoughts, complains no loves him/her) is often, sometimes, or never true of their child.

Moderator Variables	
Income Level at Wave 1 (*time-invariant*)	A continuous measure of family income (describe above) at Wave 1.
Child Age at Wave 1 (*time-invariant*)	Child age in years, as reported by the primary caregiver, at the time of the first (1997) CDS interview.
Ethnicity (*time-invariant*)	Child race/ethnicity, as reported by the parent/primary caregiver, at the initial CDS interview. Ethnicity will be effect coded (i.e., White, African American, Hispanic vs. the grand mean, which includes ethnicities other than the three coded here, e.g., Asian American).
Caregiver/Family Covariates	
Partner Status (*time-varying*)	Whether or not the primary caregiver has a spouse, partner or cohabitor who has lived with the primary caregiver for twelve months or more at the time of CDS interview, as reported by head of household.
Family Size (*time-varying*)	Total number of siblings living in the household at time of CDS interview, as reported by head of household.
Other Adults in Home (*time-varying*)	Whether or not other adults (e.g., non-partnered adults, grandparents, etc.) were living in the household at the time of the CDS interview, as reported by head of household.
Head Education Level (*time-varying*)	Head of household's self-reported number of years of completed education (ranging from 1-16, with 17 indicating at least some post-graduate education.
Employment Status (*time-varying*)	Whether or not head of household was employed at the time of CDS interview, as reported by head of household.
Welfare (*time-varying*)	Whether or not head of household received any income during the previous year from TANF, ADC, as reported by head of household.
Public Housing (*time-varying*)	Whether or not family was living in a public housing project, or whose rent was subsidized by a public agency at the time of CDS interview, as reported by head of household.
Food Stamps (*time-varying*)	Whether or not head of household or anyone in the head's family used government food stamps at any time during the year previous to the CDS interview, as reported by head of household.

Appendix C: Structural Equation Models

To check the robustness of these findings, primary analyses were also conducted using fixed effects structural equation modeling (SEM) in Stata 13.1 (StataCorp, 2013). These analyses used unimputed data in conjunction with SEM's full information maximum likelihood (FIML) option to address missing data. Figure C.1 presents the essential features of a classic fixed effects structural equation model for examining the associations between changes in income and changes in child reading scores, one of the five outcomes considered in the present research (Bollen & Brand, 2008). The equation for the fixed effects model depicted in Figure C.1 is

$$y_{it} = B_{yx}\, x_{it} + \eta_i + \varepsilon_{it}$$

where y_{it} is the outcome (e.g., reading achievement score) for individual *i* at time *t*, x_{it} is the predictor (e.g., log of the family income) for individual *i* at time *t*, B_{yx} is the coefficient that gives the association between x_{it} and y_{it} at time *t*, η_i is a scalar of all other (known and unknown) latent time-invariant variables that influence y_{it} (i.e., the fixed effects), and ε_{it} is the random error for individual *i* at time *t*. In a fixed effects structural equation model, the collection of time-invariant variables are represented by the latent variable, η, which is an unknown but fixed constant for each individual *i*. In addition, the fixed effects latent variable, η, is allowed to correlate with the time-varying predictor (as well as time-varying covariates). Finally, in a classic fixed effects structural equation model, the coefficients of the time-varying predictor (B_1 in Figure C.1) and covariates (not shown in the figure, but each with their own coefficient: B_2, B_3, etc.) are presumed not change over time, which is to say that they have the same effect each wave of data. The fixed effects time-invariant variables (η) are also presumed to have the same effect (implicit coefficient of 1) on the outcome at each wave, and the error variance is also assume to be constant over time.

Figure C.1. Fixed Effects Structural Equation Model Examining the Associations between Changes in Income and Changes in Child Reading Scores

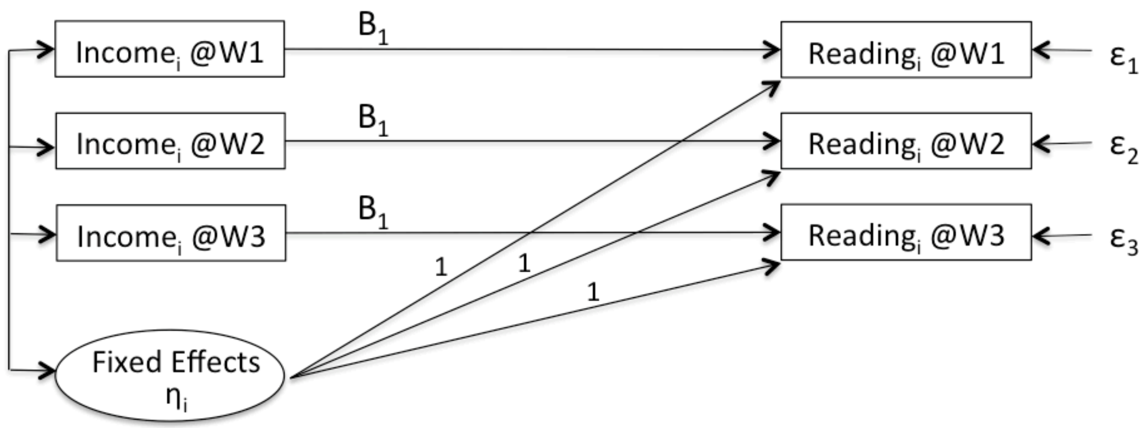


Table C.1 displays the unstandardized parameter estimates and standard errors from the structural equation models that examined the effects of family income and time-varying covariates (number of siblings, partner status of head of household, whether or not other adults were living in the home, head education, head employment status, and whether or not the family received TANF or food stamps, or were living in public housing) on child working memory, reading and math skills, and externalizing and internalizing behaviors. Model fit statistics are not available for data that use complex sampling (see Bollen Tueller, & Oberski, 2013; Maydeu-Olivares & Garcia-Forero, 2010). Coefficient of determination (CD), which can be interpreted in the same way as an R square in linear regression, is reported in lieu of summary fit statistics for the purpose of comparing models across various specifications.

The parameter estimates for this set of models were expected to be fairly comparable to those presented for the fixed effects regression models presented in Table 4. However, in light of the differences of each method for estimating missing data as well as slight differences in the structural equation model specification (e.g., allowing error variances to vary across waves) to allow for convergence, the results were not expected to be identical. Indeed, similar to the results based on the fixed effects regression models, the structural equation models also show that for the sample as a whole, prior to considering the moderators or interest, the total effects of changes in family income were not significantly associated with changes in any of the child outcomes examined.

Table C.1. Unstandardized Coefficients from Structural Equation Fixed Effects Models Examining Associations between Changes in Income and Changes in Child Cognitive, Achievement, and Socioemotional Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Log of Income	0.03 (0.02)	0.19 (0.25)	0.08 (0.17)	-0.05 (0.03)+	-0.02 (0.02)
# of Siblings	0.20 (0.08)*	5.35 (1.45)***	2.49 (1.02)*	0.50 (0.14)***	0.29 (0.11)**
Partner Status	0.12 (0.17)	2.19 (2.92)	-0.88 (2.13)	-0.21 (0.29)	-0.24 (0.24)
Other Adults in Home	-0.03 (0.08)**	-2.54 (1.23)*	-0.19 (1.05)	0.00 (0.14)	-0.23 (0.13)+
Parent Ed	0.13 (0.05)***	3.38 (1.01)***	3.00 (0.87)***	-0.20 (0.10)*	-0.18 (0.07)**
Employed	0.18 (0.18)	-2.18 (3.16)	-1.37 (2.64)	0.30 (0.36)	0.43 (0.27)
Welfare	0.86 (0.25)***	10.58 (5.64)+	4.95 (3.64)	0.37 (0.41)	0.69 (0.32)*
Public Housing	-0.00 (0.25)	-2.13 (4.59)	-5.19 (3.93)	-0.34 (0.45)	-0.16 (0.29)
Food Stamps	-0.22 (0.16)	-4.26 (3.28)	-4.27 (2.14)*	-0.43 (0.32)	0.07 (0.25)
Intercept	-2.12 (1.02)*	341.07 (16.07)***	396.40 (13.11)***	10.50 (1.84)***	5.23 (1.37)***
CD	.66	.76	.78	.77	.70

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Note. Model fit statistics are not available for data that use complex sampling (see Bollen Tueller, & Oberski, 2013; Maydeu-Olivares & Garcia-Forero, 2010). Coefficient of determination (CD), which can be interpreted in the same way as an R square in linear regression, is reported in lieu of summary fit statistics for the purpose of comparing models across various specifications.

Next, a fixed effects structural equation model was estimated that included a path from income to cumulative risk and a path from cumulative risk to the child outcome being examined, as well as a direct path from income to the child outcome. In essence, two fixed effects equations were estimated simultaneously:

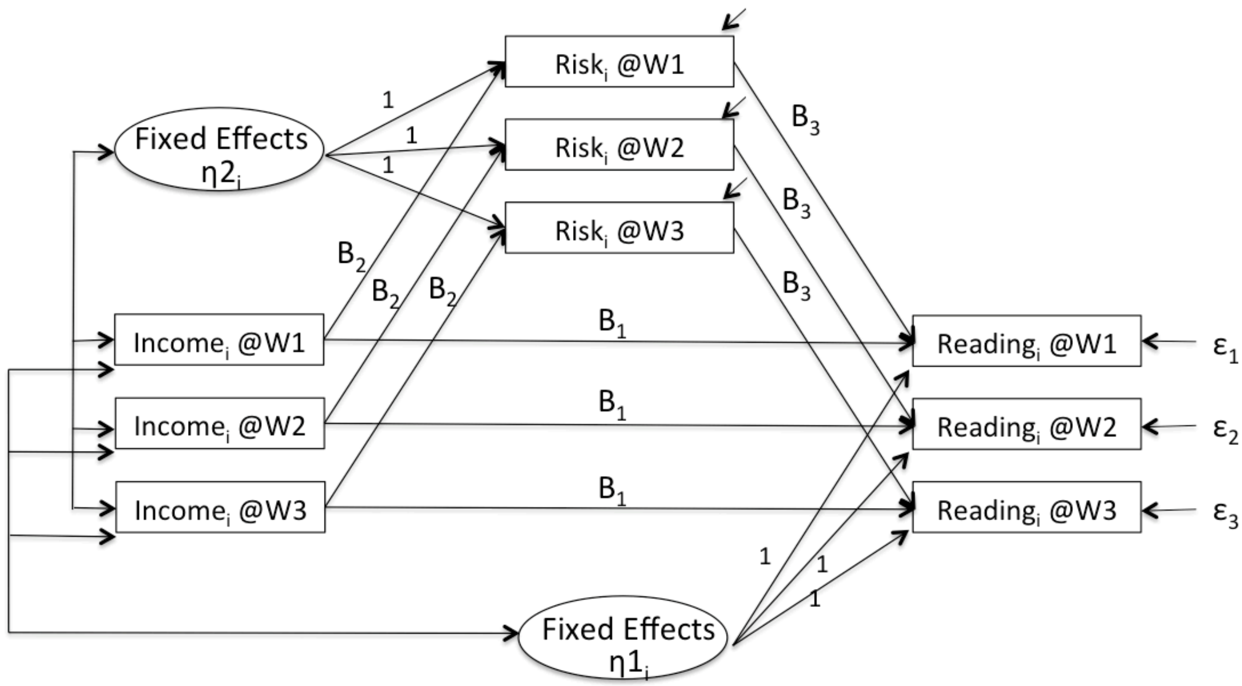
$$\mathit{Risk}_{\mathrm{it}} = \mathrm{B}_2\,\mathit{Income}_{it} + \eta 2_{\mathrm{i}} + \varepsilon_{\mathrm{it}}$$

$$\mathit{Child\ Outcome}_{\mathrm{it}} = \mathrm{B}_1\,\mathit{Income}_{it} + \mathrm{B}_3\,\mathit{Risk}_{it} + \eta 1_{\mathrm{i}} + \varepsilon_{\mathrm{it}}$$

To examine whether changes in family income was associated with changes in cumulative risk, a second fixed effects latent variable, $\eta 2$, was posited to represent the collection of all other (known and unknown) time-invariant variables that influence cumulative risk exposure. As in the classic fixed effects structural equation model, this second latent variable is allowed to correlate with the time-varying predictor (i.e., family income). And again, the coefficients of the time-varying predictor in this model (B_2 in Figure C.2), the fixed effects time-invariant variables ($\eta 2$), and the error variance are presumed to be constant over time.

To examine whether changes in cumulative risk were associated with changes in child outcomes (above and beyond those associated with changes in income), cumulative risk was added to the previous income-only (plus covariates) fixed effects structural equation model. Income was also retained as a covariate, to examine both the effects of cumulative risk over and above that of income, as well as to estimate the residual direct effects of income on each outcome. Figure C.2 presents the essential features of a fixed effects structural equation mediation model for examining the associations between changes in income, changes in cumulative risk, and changes in child reading scores, one of the five outcomes considered in the present research.

Figure C.2. Fixed Effects Structural Equation Mediation Model Examining the Simultaneous Associations between Changes in Income, Changes in Cumulative Risk, and Changes in Child Reading Scores



Results for the fixed effects structural equation mediation model indicated that changes in family income were significantly associated with changes in cumulative risk (β = -0.26, SE = 0.04, $p < .001$), with increases in family income predicting decreases in cumulative risk. The effect size for the changes in income on changes in cumulative risk is moderate (-0.31). Table C.2 displays the unstandardized parameter estimates from the structural equation models that simultaneously examined the effects of family income, cumulative risk and time-varying covariates on child working memory, reading and math skills, and externalizing and internalizing behaviors. The addition of cumulative risk to the model explained an addition 19% of the variance in working memory, an additional 14% of the variance in reading scores, an additional 12% of the variance in math scores, an additional 12% of the variance in externalizing, and an additional 16% of the variance in internalizing behaviors. Similar to the results reported for the fixed effects regression analyses, decreases in cumulative risk were significantly associated with increases in children's reading and math skills and decreased externalizing behaviors. Effects sizes were small (-0.05 for reading and math, and 0.17 for externalizing). In the structural equation models, decreases in cumulative risk were also significantly associated with decreased internalizing behaviors (effect size was also small, at 0.16).

Table C.2. Unstandardized Coefficients for Structural Equation Fixed Effects Models Examining Associations between Changes in Income, Changes in Cumulative Risk, and Changes in Child Cognitive, Achievement, and Socioemotional Outcomes

Time-Varying Variables	Working Memory	Reading	Math	Externalizing	Internalizing
Cumulative Risk	-0.20 (0.21)	-5.55 (2.60)*	-4.20 (1.94)*	2.33 (0.39)***	1.54 (0.48)***
Log of Income	0.03 (0.02)	0.18 (0.26)	0.10 (0.17)	-0.03 (0.03)	-0.01 (0.02)
# of Siblings	0.21 (0.08)*	5.62 (1.47)***	2.72 (1.03)**	0.37 (0.14)**	0.20 (0.11)+
Partner Status	0.11 (0.17)	1.74 (2.95)	-1.27 (2.16)	-0.06 (0.30)	-0.14 (0.24)
Other Adults in Home	-0.03 (0.08)	-2.46 (1.23)*	-0.14 (1.05)	-0.04 (0.14)	-0.25 (0.13)+
Parent Ed	0.13 (0.05)**	3.33 (1.01)**	2.96 (0.87)***	-0.21 (0.10)*	-0.19 (0.07)**
Employed	0.18 (0.18)	-2.15 (3.16)	-1.36 (2.63)	0.26 (0.36)	0.40 (0.27)
Welfare	0.84 (0.25)***	10.13 (5.57)+	4.64 (3.61)	0.54 (0.41)	0.80 (0.31)*
Public Housing	-0.00 (0.25)	-2.12 (4.55)	-5.19 (3.91)	-0.33 (0.43)	-0.16 (0.28)
Food Stamps	-0.20 (0.16)	-3.76 (3.26)	-3.87 (2.12)+	-0.56 (0.32)+	-0.17 (0.25)
Intercept	-2.05 (1.01)*	445.48 (16.44)***	396.47 (13.41)***	9.37 (1.83)***	4.45 (1.39)***
CD	.85	.90	.90	.89	.86

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Note. Model fit statistics are not available for data that use complex sampling (see Bollen Tueller, & Oberski, 2013; Maydeu-Olivares & Garcia-Forero, 2010). Coefficient of determination (CD), which can be interpreted in the same way as an R square in linear regression, is reported in lieu of summary fit statistics for the purpose of comparing models across various specifications.

Finally, direct and indirect effects of income, through cumulative risk, were calculated for child working memory, reading and math achievement, and externalizing and internalizing behaviors. Coefficients and standard errors for income effects with and without cumulative risk in the model are presented in Table C.3. Results again indicate small but significant indirect effects of changes in income through changes in cumulative risk on reading and math achievement, and externalizing scores (supporting the corresponding results of the fixed effects regression models presented in Table 7), as well as internalizing scores.

Table C.3. Direct and Indirect (through Cumulative Risk Exposure) Effects of Income on Child Outcomes

	Income Only + Controls	Cumulative Risk Exposure Added	
	Direct Effect of Income	*Direct Effect of Income*	*Indirect Effect of Income thru CR*
Working Memory	0.03 (0.02)	0.03 (0.02)	0.00 (0.00)
Reading	0.19 (0.25)	0.18 (0.26)	0.07 (0.04)*
Math	0.08 (0.17)	0.10 (0.17)	0.06 (0.03)*
Externalizing	-0.05 (0.03)+	-0.03 (0.03)	-0.03 (0.01)***
Internalizing	-0.02 (0.02)	-0.01 (0.02)	-0.02 (0.01)***

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$

Note. In addition to the indirect effects of income through cumulative risk (CR), there were also indirect effects of income through the fixed effects, η2, associated with cumulative risk. These were in the opposite direction of the indirect effects of income through cumulative risk (i.e., negative for cognitive/academic outcomes and positive for socioemotional outcomes).

Appendix D: Lagged Structural Equation Analytic Techniques

As noted above in the main text, structural equation modeling offered an opportunity to fairly easily examine whether changes in income and/or changes in cumulative risk may have a lagged effect on changes in child outcomes, as suggested by previous research (Thomson, Dearing, & Coley, unpublished). For the first set of these "lagged" models, changes in income (and time-varying covariates) between Waves 1 and 2 were used to predict changes in child outcomes between Waves 2 and 3. The second set of lagged models adds a path in which changes in income between Waves 1 and 2 predict changes in cumulative risk between Waves 1 and 2, and a path in which changes in cumulative risk between Waves 1 and 2 predict changes in child outcomes between Waves 2 and 3. Thus, the lagged models replicate the structural equation models presented above but with the dependent variables (the child outcomes) being lagged (see Figures D.1 and D.2). The disadvantage of these lagged models are that there are effectively only two time points in these models. Nonetheless, they allow for the exploration of the possibility that within-child changes in income and/or cumulative risk may have a delayed or more long-term effect on child outcomes.

Figure D.1. Lagged Fixed Effects Structural Equation Model Examining the Associations between Changes in Income and Changes in Child Reading Scores Five Years Later

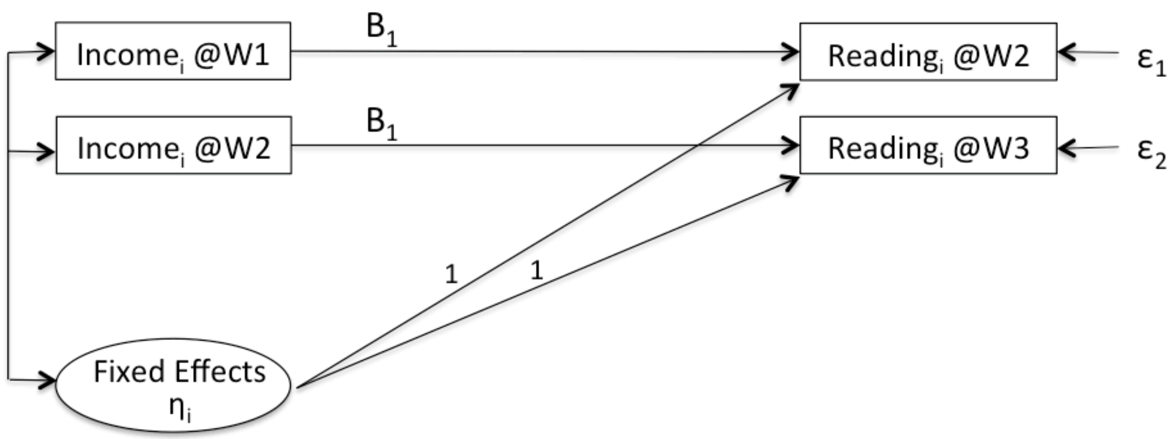
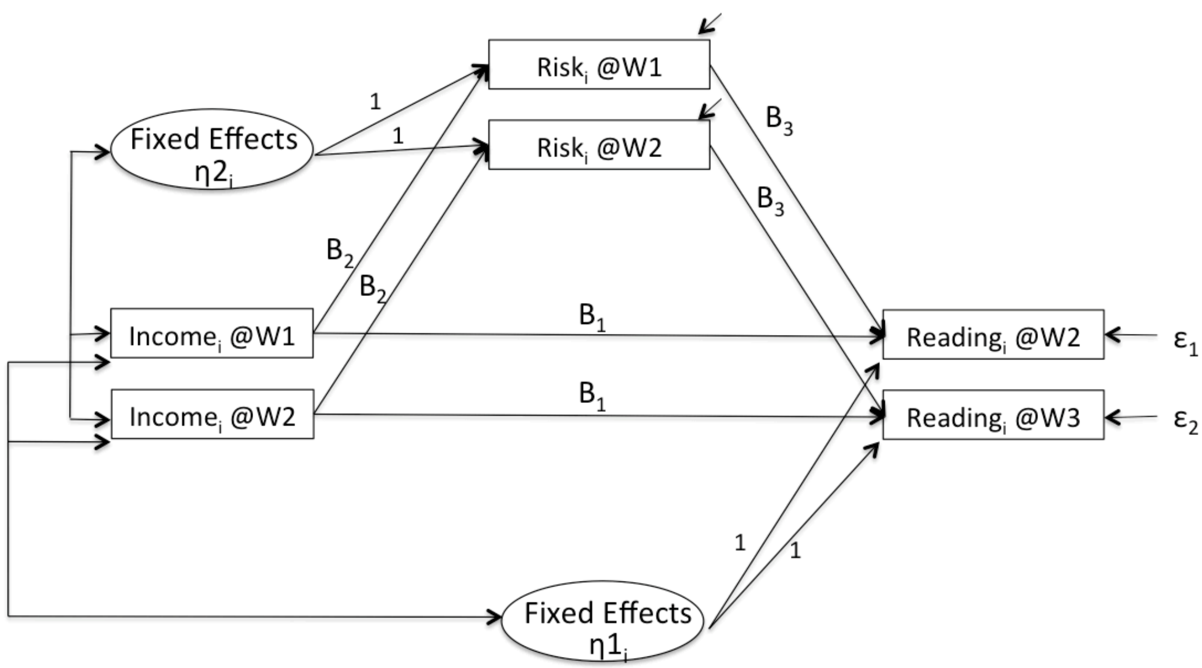


Figure D.2. Lagged Fixed Effects Structural Equation Mediation Model Examining the Simultaneous Associations between Changes in Income, Changes in Cumulative Risk, and Changes in Child Reading Scores Five Years Later



Appendix E: Alternative Model Specifications

Both sets of primary analyses (regression and structural equation models) were also run without controlling for welfare, housing assistance, or food stamps receipt. The addition of these covariates to the model slightly decreased the income coefficients, but did not significantly affect overall results.

In addition, alternative measures of both income and cumulative risk were explored. With respect to income, a measure of "permanent" income, in comparison to the contemporaneous income measure used in the above analyses, was investigated. The measure of permanent income was an average of the family income across the five years prior to each data collection time point. While a measure of permanent family income has the advantage of perhaps better representing more stable, or longer lasting, changes in family income levels, rather than the potentially idiosyncratic shocks to family income that may be reflected in a contemporaneous income measure at any given point in time, it was found that the greater stability of permanent income was a disadvantage for fixed effects models, as they did not adequately capture the fluctuation in a family's economic circumstances.

An alternative measure of cumulative risk exposure was also explored. The above analyses used a "threshold" measure of risk, in which individual risk indicators reflected whether a child's exposure to that particular contextual risk (e.g., neighborhood safety) was high (dummy coded 1) or not (dummy coded 0). For example, if a head of household responded to the question, "How safe is it to walk around alone in your neighborhood after dark?" by saying it was "somewhat dangerous" or "extremely dangerous," the child's level of risk for this indicator would have been coded as high, or present (i.e., dummy coded as 1), whereas if the head of household responded that it was “fairly safe” or “completely safe,” the threshold measure for this indicator would be low or not present (i.e., dummy coded as 0). A continuous measure of cumulative risk, in comparison to the threshold measure, was investigated as well. For the continuous measure of risk, individual risk indicators reflected a more incremental level of risk from less to more, rather than low/not present vs. high/present. In the example above, if the head of household said that it was “completely safe” to walk around alone in their neighborhood after dark, this would have been coded as 0 on the continuous measure, “fairly safe” would have been coded as 1, “somewhat dangerous” would have been coded as 2, and “extremely dangerous” would have been coded as 3, such that the level of risk could have ranged from 0, indicating no risk, to 3, extremely high risk, with possible values in between as well.

While the continuous measure of risk had the potential to contain more information about a child’s level of exposure to risk, it was unclear whether smaller, more incremental changes in risk were of practical significance. In other words, does, for example, moving from a neighborhood that is “fairly safe” to a neighborhood that is “completely safe” matter in a way that might have an effect on child outcomes? Indeed, the continuous measure of cumulative risk produced much more sporadic, inconsistent results, particularly with respect to children’s cognitive/academic outcomes.

Appendix F: Fixed Effects vs. Random Effects

Hausman tests were conducted for each outcome to examine whether it might be appropriate to combine fixed effects and between effects into a random effects model, which can sometimes be less consistent but also has the potential to be a more efficient model with lower standard errors. For each outcome, it was found that fixed effects (presented in Table 4) and random effects coefficients (presented below in Table F.1) differed significantly. This indicates that within-child changes in income have significantly different magnitudes of effects on child outcomes than between-child differences, and thus that random effects models were not appropriate.

Table F.1. Regression Coefficients from Random Effects Models Examining Associations between Income and Child Cognitive, Achievement, and Socioemotional Outcomes

Time-Varying Variables	**Working Memory**	**Reading**	**Math**	**Externalizing**	**Internalizing**
Log of Income	0.07 (0.01)***	1.11 (0.26)***	0.97 (0.19)***	-0.04 (0.03)	-0.00 (0.02)
# of Siblings	0.08 (0.04)*	3.93 (0.68)***	3.08 (0.51)***	0.06 (0.07)	0.07 (0.05)
Partner Status	0.10 (0.09)	1.32 (1.69)	1.22 (1.24)	-0.42 (0.17)*	-0.20 (0.13)
Other Adults in Home	-0.07 (0.05)	-3.22 (1.03)**	-2.27 (0.74)**	0.10 (0.10)	-0.03 (0.08)
Parent Ed	0.08 (0.02)***	1.86 (0.35)***	1.36 (0.26)***	-0.13 (0.04)***	-0.11 (0.03)***
Employed	0.10 (0.11)+	3.21 (2.00)	1.05 (1.44)	0.12 (0.19)	0.29 (0.15)*
Welfare	-0.02 (0.16)	-7.02 (3.04)*	-3.96 (2.17)+	0.07 (0.29)	0.25 (0.22)
Public Housing	-0.05 (0.13)	0.67 (2.42)	0.13 (1.75)	0.15 (0.24)	0.07 (0.18)
Food Stamps	-0.18 (0.11)	-6.96 (2.06)**	-6.33 (1.48)***	-0.03 (0.20)	0.17 (0.15)
Wave/Time (in years)	0.44 (0.01)***	13. 16 (0.14)***	9.15 (0.10)***	-0.07 (0.01)***	0.09 (0.01)***
Intercept	-3.89 (0.80)***	3.06.42 (15.17)***	357.64 (11.17)***	10.24 (1.54)***	3.55 (1.14)**

*** $p < .001$; ** $p < .01$; * $p < .05$; + $p < .10$