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The Influence of Adverse Childhood Experiences, Families, Neighborhoods, and School Environments on Cognitive Outcomes among Schoolchildren

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THE INFLUENCE OF ADVERSE CHILDHOOD EXPERIENCES, FAMILIES, NEIGHBORHOODS, AND SCHOOL ENVIRONMENTS ON COGNITIVE OUTCOMES AMONG SCHOOLCHILDREN

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ABSTRACT

Schools, families, and neighborhoods can support the development of happy, healthy children and adolescents. However, a majority of children in the United States also experience adversity in their early lives that can have deleterious effects on their cognitive and socioemotional development. Measuring and modeling early adversity is fundamental to understanding development as it occurs through interactions with schools, families and neighborhoods. As outlined by Bronfenbrenner's bioecological model of human development, proximal and distal forces shape development, and cannot be isolated when relating measures of the developmental context to outcomes for individuals. For schools and other social programs to support students from high adversity backgrounds, the nature and structure of adversity and contextual influences must be measured and modeled in a robust manner.

The three distinct papers in this dissertation describe the construction and evaluation of measurements for adversity, family conflict, neighborhood quality, and school safety, along with models that relate these elements to each other and cognitive outcomes in childhood and adolescence. Structural equation modeling is used to investigate the latent variables generated to measure the constructs and the nature of their relationships. The studies use nationally representative data from the Panel Study of Income Dynamics to create and test the theoretically driven models. The first study constructs and tests latent variables aligned with the Adverse Childhood Experiences (ACEs) framework in order to generate a continuous and theoretically coherent measurement of adversity. The second study uses this ACEs measurement along with measures of family conflict and neighborhood quality to generate and test path models informed by the bioecological theory of development. The third study applies these measures of developmental constructs to the study of safety in schools and identifies the differential function of school safety for children with varying levels of adversity to better understand the potential for school-based interventions.

Results from these studies indicate the utility of a latent variable approach to measuring adversity, and the viability of path analysis for the study of how ACEs, family conflict and neighborhood quality influence cognitive outcomes. Additionally, results provide evidence for the necessity of varied and networked developmental supports for children from highly adverse beginnings, above those that may be available through reforms to school safety. Taken together, these studies provide a rich portrait of childhood development incorporating multiple contextual influences, and add to our understanding of what schools can and cannot do to support children.

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CHAPTER 1

Introduction

More than half of the children in America experience adversity in the early years of their lives (Center for Disease Control and Prevention, 2015; Felitti et al., 1998). These experiences include physical, emotional, and sexual traumas that have impacts throughout one's life course. Childhood adversity is predictive of mental and physical health in adulthood (Center for Disease Control and Prevention, 2015; Felitti et al., 1998; Felitti & Anda, 2010). Antecedent to these adult outcomes, the impact of adversity is apparent in adolescence and childhood (Bethell, Newacheck, Hawes, & Halfon, 2014; Finkelhor, Shattuck, Turner, & Hamby, 2015; Schilling, Aseltine, & Gore, 2007; Thompson et al., 2015). This early childhood adversity has negative impacts on a child's cognitive and socio-emotional development and potential (Brooks-Gunn & Duncan, 1997; G. J. Duncan & Murnane, 2011; Jaffee & Maikovich-Fong, 2011; Thompson et al., 2015). However, although adversity has been shown to have deleterious effects at multiple developmental stages, an individual's early adversity cannot be fully understood without also understanding the context of development (Bronfenbrenner & Morris, 2006; Darling, 2007; Sameroff, 2010).

A more robust understanding of child development can be constructed by incorporating considerations of the child's home and family life (Cicchetti, 2013). Children exposed to familial conflict experience negative cognitive and socio-emotional outcomes (Clarkson Freeman, 2014; S. E. Evans, Davies, & DiLillo, 2008; Forehand, Biggar, & Kotchick, 1998). These families do not exist in isolation, and the interplay between families and their neighborhood contexts is complex and mixed (Briggs, Popkin,

& Goering, 2010). Neighborhoods are a proximal developmental influence with which children interact in different ways at different stages of their development (Bronfenbrenner, 1994; Sameroff, 2010). Characteristics of neighborhoods have been shown to have positive and negative influences on developmental outcomes (Leventhal & Brooks-Gunn, 2000; Sharkey & Faber, 2014). In addition to families and neighborhoods, beginning in early childhood children interact with schools in ways that greatly influence their ongoing development (Bronfenbrenner, 1976; Eccles & Roeser, 2011). Schools interact with these other contexts and have the potential to influence or mediate the effects of adverse conditions (Altonji & Mansfield, 2011; Eccles & Roeser, 2010).

The proximal contextual influences of families, neighborhoods, and schools can be mapped in a coherent manner using the bioecological understanding of human development (Bronfenbrenner, 1976, 1996; Bronfenbrenner & Morris, 2006). This model of development argues that the nature of these contexts and their relationships shape individual outcomes (Bronfenbrenner, 1996). The bioecological model of development interprets proximal and distal contexts, through the individual's interactions with these contexts and their interactions with each other, as driving child development (Bronfenbrenner & Evans, 2000; Bronfenbrenner & Morris, 2006). This bioecological perspective is used domestically and globally to frame research related to human development and public health (Blas & Kurup, 2010; US Department of Health and Human Services, 2010). Adversity research and educational outcomes should acknowledge the multi-level structure that effect children's lives (Darling, 2007; Feinstein, Duckworth, & Sabates, 2008). Families, neighborhoods, and schools are all proximal contexts that shape a child's development through direct interaction (Berns, 2010; Bronfenbrenner, 1994; Eccles & Roeser, 2010). As a guiding framework in research, a bioecological perspective requires research that is not bound by measures of the individual, but rather examines larger contexts and their interactions with the individual (Bronfenbrenner, 1976). Research relating adversity and educational outcomes should integrate the presence of multiple risk factors, as they co-occur and interact (Bronfenbrenner, 1996; Cassen, Feinstein, & Graham, 2009; Darling, 2007; Dong et al., 2004).

The overarching purpose of the sequence of studies in this dissertation is to construct and describe a statistical model relating childhood adversity to cognitive outcomes in childhood and adolescence. Guided by the bioecological model of human development, measures of families, neighborhoods, and schools are included in order to account for their complex connections. The first study creates a new measure of childhood adversity modeled after a widely used framework for the construct. The second study incorporates measures of family conflict and neighborhood quality to build and test a complex bioecological model of development. The third study introduces the school environment into the model and measures the ability of schools as safe places to serve as a resource or protective factor for children from highly adverse backgrounds. In order to measure and craft policy related to adversity and its relation to educational and behavioral outcomes, it is important for the risks, potential protective factors, and their complex connections to be better understood (Fergus & Zimmerman, 2005).

These studies utilized data from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal study created by the US Department of Labor which has collected information about the economic, educational, and social lives of American families since its inception in 1968 (McGonagle, Schoeni, Sastry, & Freedman, 2012). The child development supplement (PSID-CDS) was conducted in three waves from 1997 - 2007 to collect information about the lives and experiences of children in the families that made up the PSID sample. The PSID-CDS collected information on over 500 indicators on children related to their home environments, their relationships with family and community, and their experiences in school. Children, primary and secondary caregivers, teachers, school administrators, and day-care providers all served as informants as to the early life experiences of the children. These data were used to construct measures of the constructs of interest in these studies. The PSID-CDS is a nationally representative data set that can be used to model these complex relationships as they naturally occur (Ginther, Haveman, & Wolfe, 2000; McGonagle et al., 2012). The use of this data set to address these issues using frameworks native to the individual fields of study (e.g. neighborhood effects, adverse childhood experiences) represents an innovative approach to measuring and understanding the impact of adversity on children embedded in their personal contexts.

The central statistical approach utilized in these studies was structural equation modeling (SEM). SEM is a group of statistical procedures that allow theory-based hypothesized relationships between observed and latent variables to be tested with non-experimental data (Kline, 2015; Pearl, 2012). The studies used confirmatory factor analysis (CFA), a branch of SEM that focuses on the relationship between observed measures and theoretical models (T. A. Brown, 2015). CFA was used to construct and evaluate latent variables corresponding with adversity, families, neighborhoods, and schools. A latent variable is a variable that is indirectly observed through the sample values of observed variables (Bollen, 2002). These latent variables were related using path models to examine their relationships using full structural equation modeling techniques (Kline, 2015). Structural equation modeling also allows for the evaluation of the presence and stability of meditational effects on the relationships between adversity and cognitive outcomes by these contextual factors (Cole & Maxwell, 2003).

This dissertation serves to address a number of openings in the continued study of human development and adversity using the bioecological model. First, as noted by Evans and colleagues (2013), measurement models of childhood adversity most frequently employ index approaches to determining an adversity measurement. The first study joins an emerging strand of research utilizing a latent variable approach to constructing measurements of adversity from existing data sets (M. J. Brown, Perera, Masho, Mezuk, & Cohen, 2015; Ford et al., 2014; Guinosso, Johnson, & Riley, 2016). Although composite measurements of adversity have previously been constructed from the PSID-CDS data (e.g., Björkenstam et al., 2015; Ciula & Skinner, 2015), this study represents the first time a latent variable approach has been used to measure the construct using this data. Second, this study adds to the growing but still malleable field of developmental science governed by the bioecological model. According to Bronfenbrenner & Morris (2006), bioecological development research that occurs in "discovery mode" is theoretically driven and should increase in complexity, with the theoretical implications serving as vital outcomes. In these studies, increasingly complex interactions among the variables are constructed along theoretical lines and tested. Finally, the potential for contextual elements of schools to provide a protective factor for students from highly adverse backgrounds have yielded mixed results (Hong & Eamon, 2012; McEwin & Greene, 2010; Tanner-Smith & Fisher, 2016). Such studies have not focused on pre- and young adolescents while employing multiple developmental influences to focus on school environments (Ciula & Skinner, 2015; Thompson et al., 2015). This research incorporates a measure of school safety into a larger developmental model with a sample of elementary and middle school students. By incorporating vital measures of proximal influencers guided by a bioecological framework, the studies in this dissertation provide evidence to further untangle the relationships among these variables. In order to provide such evidence, a number of questions were systematically addressed over the course of the studies contained in the following chapters.

Research Questions

Using SEM to generate models based on the bioecological model of human development, these studies used data from the PSID-CDS to measure and relate childhood adversity, family conflict, neighborhood quality, school safety, and cognitive outcomes. Consequentially, the following articles addressed a number of research questions:

Article One: A New Measurement of Adverse Childhood Experiences drawn from the Panel Study of Income Dynamics Child Development Supplement

1) Is a theoretically-constructed latent measurement model for adverse childhood experiences (ACEs) able to reproduce the relationships between variables present in the PSID-CDS data?
2) Is this measurement generalizable across groups classified by race, gender, and age?

Article Two: Childhood Adversity, Families, Neighborhoods, and Cognitive Outcomes: Structural Models of the Bioecological Framework

3) When modeled using ACEs, family conflict, and neighborhood quality, what is the nature of the path coefficients from the individual, families, and neighborhoods to cognitive outcomes?
4) Are the relationships between the family and neighborhood contexts and cognitive outcomes better modeled as a direct pathway or as indirect pathways through the individual as measured by ACEs, consistent with the bioecological model of development?

Article Three: The Role of School Safety Factors in Supporting Pre- and Young Adolescents with Adverse Backgrounds

5) Are increases in the school safety conditions related to cognitive functioning of students in kindergarten to seventh grade when schools are modeled as a microsystem functioning through the individual?
6) Is the relationship between school safety and cognitive outcomes different for students from high adversity backgrounds when compared to students from lower adversity backgrounds?

Significance

The purpose of this research was to provide additional understanding of the relationship between childhood adversity and cognitive outcomes in youth. The methodological approach using SEM to model childhood adversity and human development through a bioecological lens is a new application of the PSID-CDS data. The variables and techniques used in this study could serve as additional evidence for the suitability of this type of employment of the data set. The PSID is a robust data set with rich indicators collected longitudinally. The approach to modeling adversity, family conflict, neighborhood quality, and school safety using the data set could be co-opted by other researchers who make use of the PSID. This could increase the overall utility of the data set and bring new professionals from diverse fields into the PSID research community. While the PSID has been utilized to answer many longitudinal questions related to the economic lives of adults, the approaches in this study provide an example of investigating questions related to earlier life course outcomes.

By incorporating developmentally important elements of context, the findings from these studies provide a fine-grained understanding of what schools can do, and what they cannot. The cognitive levels of pre- and young adolescents that are the outcome variables in these studies have implications for the ongoing success of young adults at they move through their secondary education and into economic and social independence (Balfanz et al., 2014; Balfanz, Herzog, & Mac Iver, 2007). A better understanding of adverse experiences will allow researchers and policymakers to craft and implement interventions that address early adversity. This program of research is also intended to provide support for structures that can mediate the effects of adverse childhood experiences within existing school settings. Interventions of this type can help reduce the perpetuation of inequalities stemming from differences in the early lives of children.

CHAPTER 2

A New Measurement of Adverse Childhood Experiences drawn from the Panel Study of Income Dynamics Child Development Supplement

Introduction

Nearly two thirds of children in the United States experience adverse experiences in their childhood (Center for Disease Control and Prevention 2015; Felitti et al. 1998). As classified by Felitti and colleagues (1998), adverse childhood experiences (ACEs) are a set of experiences of abuse and household dysfunction which have been demonstrated as being antecedents to numerous negative physical and mental health outcomes in adulthood (Felitti et al. 1998; Felitti and Anda 2010). The ACEs framework consisting of discrete indicators allows for the early identification of children who are likely to experience their deleterious effects. As use of this framework expands to address questions that intersect with diverse disciplines (e.g., Fry-Geier and Hellman 2016; Larkin et al. 2014) and global contexts (e.g., Kezelman and Stavropoulos 2012; Park and Chung 2013; Reuben et al. 2016), it is important to identify tenable methods for creating measurements of ACEs. This study uses a sample of children that is representative of the US population to construct a measurement of ACEs using a latent variable approach. This method is recently emergent in ACEs research (Evans et al. 2013; Ford et al. 2014; Guinosso et al. 2016), and is compared here to more widely used methodological approaches. By continuing to refine the ways in which adversity is measured, researchers can better understand adversity and relate ACEs to physical, cognitive, and behavioral outcomes.

Defining ACEs

The adverse childhood experiences (ACEs) framework is a widely used tool to conceptualize and categorize experiences in childhood with deleterious repercussions in adulthood. The original ACEs study conducted by Felitti and colleagues (1998) collected questionnaire data from visitors to a medical evaluation center associated with insurance customers in a major US city. Visitors to the medical center were sent a questionnaire by mail in the weeks following their appointment, which inquired about childhood experiences. Survey data collected over two waves was then linked with medical histories collected in the clinical setting, constituting the data for further analysis. The data from this study was used to demonstrate the correlation between ACEs and adult outcomes such as smoking (Anda et al. 1999), drug use (Dube et al. 2003), sexually transmitted disease (Hillis et al. 2000) risk of suicide (Dube et al. 2001), and overall personal health (Felitti et al. 1998). Since this original study, the ACEs framework has been used by numerous researchers, and is employed by the Center for Disease Control and Prevention as their measurement of child maltreatment.

The ACEs framework originally included seven types of experiences in two categories. The abuse category consisted of psychological abuse, physical abuse, and sexual abuse. The household dysfunction category included violence against the mother, living with individuals with substance abuse problems, living with mentally ill/suicidal individuals, and living with previously incarcerated individuals. In the original ACEs study, each item was indicated by one to four questions, and a positive response on any question was measured as a positive response to the broader item (Felitti et al. 1998). These questions were a mixture of items adapted from earlier surveys and newly generated items (Anda et al. 2006; Felitti et al. 1998). In the 1998 study, over half of the respondents reported experiencing at least one ACE in their childhood (Felitti et al. 1998). Further investigation found that these experiences are unlikely to occur in isolation; all of the categories were positively correlated with each other (Dong et al. 2004).

The negative impact of ACEs has been shown to be measurable during childhood and adolescence. Similar to studies of adults, teens who reported adverse experiences were more likely to experience depression, drug abuse, and antisocial behavior in young adulthood (Schilling et al. 2007). Adolescent children who reported adverse experiences also reported a higher rate of anger, depression, anxiety, and dissociation (Finkelhor et al. 2013). These individuals have also been shown to have lower rates of engagement at school (Bethell et al. 2014). The persistent occurrence of ACEs has greater negative effects on IQ, and internalizing and externalizing behaviors than limited occurrences. (Jaffee and Maikovich-Fong 2011). The multidimensional nature of adversity and its connections to other contextual elements are apparent early in a child's life (Hindman et al. 2010). However, the path of influence of adverse experiences through childhood and adolescence remains poorly traced (Ciula and Skinner 2015), with emerging research further investigating the dimensionality of childhood adversity through differential physiological effects (McLaughlin et al. 2014).

Measuring ACEs

Due to the sensitive nature of ACE indicators, measuring ACES provides challenges for sampling and study design. The original ACE study depended on individuals self-reporting incidents of these experiences later in life (Felitti et al. 1998). Although this is convenient for data collection, such structures often suffer from recall bias (Widom et al. 2004). However, there is a growing body of research utilizing existing data sets that collect indicators aligned with the ACE framework from adults in those children's lives. Stambaugh and colleagues (2013) constructed a crosswalk between the ACEs framework and data from the National Survey of Child and Adolescent Well-Being (NSCAW). The NSCAW samples children that have been reported to the child welfare system. The study identified elements from interviews with caseworkers and caregivers that are aligned with the ACEs items (Stambaugh et al. 2013). Similarly, as reported by Bethell and colleagues (2014), the 2011-2012 National Survey of Children's Health (NSCH) contained nine items deemed to be aligned with the ACEs framework. Items in the NSCH were completed by parents or other caregivers. Björkenstam and colleagues (2015) utilized adult report data from the Panel Study of Income Dynamics (PSID) to indicate the presence or absence of ACEs. Although these studies use diverse data sets, they construct measurements of ACEs in similar ways.

Approaches to measuring ACEs typically employ a cumulative risk approach where framework-aligned variables are reduced to binary indicators of presence/absence, and the indicators are summed (Evans et al. 2013). This value is then used in models that incorporate other variables of interest. This approach was used in the original ACEs study (Felitti et al. 1998) along with studies that use indicators aligned with the ACEs framework (e.g., Björkenstam et al. 2015; Moore and Ramirez 2015; Stambaugh et al. 2013). This approach is parsimonious and able to be used with small samples; however, it constrains the individual ACEs to equal influence on the outcomes (Evans et al. 2013). A similar approach, in which all indicators are standardized and their z-scores are summed, suffers many of the same limitations (Evans et al. 2013).

Regression approaches to measuring ACEs have been demonstrated to explain more variance in the outcomes than approaches that use a cumulative risk approach (Burchinal et al. 2000). This type of approach models individual ACE indicators as independent variables in a regression equation, allowing for each indicator to influence the outcome separate to the others. However, as noted by Guinosso and colleagues, (2016), regression approaches can present challenges to interpretability. These issues are heightened with smaller sample sizes, and ACEs indicators may not reach statistical significance (Evans et al. 2013) Additionally, many ACEs may be collinear creating issues within the model.

Recently, some authors working with ACEs have begun to use a factor analysis approach (Guinosso et al. 2016). This approach models ACEs as a latent factor as measured by individual indicators. A latent variable is a variable for which there is no direct measurement for at least some observations in a given sample (Bollen 2002). The values of latent variables are indirectly observed through the sample values of observed variables, or indicators. The construction of such latent variables is driven by theory and can be tested empirically (Bollen 2002; Brown 2015). This emergent approach has been used to construct a measure of ACEs using nationally representative surveys with larger sample sizes, with promising results (Ford et al. 2014). Very recently, the factor analysis approach has been used in an applied manner to model negative outcomes in adulthood (e.g., Brown et al. 2015).

Purpose of This Study

The purpose of this study is to construct a latent measure of ACEs using a confirmatory factor analysis (CFA) approach from the Panel Study of Income Dynamics

Child Development Supplement (PSID-CDS) data from the 2002 wave of collection (Survey Research Center 2016). Rather than using the commonly employed summation of dichotomous risk factors (Evans et al. 2013), this model follows the presence of subcategories in the original ACEs framework (Felitti et al. 1998; Felitti and Anda 2010) and allows for the variance in the indicators to be maintained. This allows for comparisons to a single factor approach and approaches wherein the scale and weight of indicators are treated in a homogenous way. This study expands on the limited literature using the PSID-CDS to investigate childhood adversity. Although previous authors have employed the PSID-CDS to investigate questions related to adversity in childhood (e.g., Björkenstam et al. 2015; Ciula and Skinner 2015), this study extends on that foundation by selecting indicators specifically aligned with the ACEs framework and by using CFA methodology to demonstrate the fit of indicators into the framework.

Method

Data

The Panel Study of Income Dynamics (PSID) is a longitudinal study created by the US Department of Labor which has been collecting information about the economic, educational, and social lives of American families since its inception in 1968 (McGonagle et al. 2012). The child development supplement (PSID-CDS) was added in 1997 to collect information about the lives and experiences of the children in the families that made up the sample. The initial wave collected information on over 500 indicators related to their home environments, relationships with the families and community, and their experiences in school. Primary caregivers participated in face-to-face interviews with PSID-CDS field agents, and children completed interview and standardized assessments (Hofferth et al. 1997). The use of multiple informants to provide information on numerous indicators led to rich data on these children's individual developmental contexts. The PSID-CDS was collected in 1997, 2002, and 2007. The 2002 data was selected for this study as the data was more complete than the 1997 due to changes in collection procedures, and the 2002 sample size was larger than the 2007 collection due to children aging out of the study.

Sample. In 2002, 3271 children were eligible for the sample. Of this sum, interviews with primary caregivers (PCGs) were completed on 2907 children, a 91% response rate. The 2002 data was selected for this analysis due to a number of advantageous features, including low rates of missing data on the variables of interest and a sample aged past early childhood (ages 0-4), allowing for greater interpretability of the meaning of indicators which may be ambiguous for young children, such as verbal affection directed at the child. The PSID-CDS provides weights that adjust the sample to remain nationally representative with respect to race, education level of the head of the household, urbanicity, and census region. As recommended by the technical documentation, as this analysis involves child-level data and data involving the relationship of the child with a caregiver or with family characteristics, the primary caregiver/child weight was employed (Gouskova 2001, p. 3).

ACEs Variables. Adverse childhood experiences were measured using thirteen variables from the PSID-CDS aligned with the ACEs framework (Felitti et al. 1998; Felitti and Anda 2010). The variables were selected due to their alignment with the original ACEs framework. Although other researchers have branded a wide variety of childhood experiences as ACEs (e.g., Björkenstam et al. 2015; Finkelhor et al. 2015), this study selected variables aligned with the original framework. This approach allows for the employment of this measure in additional studies that can be interpreted in relation to the existing robust body of ACEs research. These variables are presented in Table 2.1.

The variables aligned with the household dysfunction category of ACEs included measures of violence, emotional distress, substance abuse and household composition. Presence of both the child's biological mother and father in the home was indicated using a binary variable constructed from the demographic file associated with the child. A variable of household violence was indicated by the primary caregiver indicating the extent to which he/she agreed with the statement, "family members sometimes hit each other." This item was drawn from the National Survey of Families and Households (Sweet et al. 1988). A dichotomous variable indicating problematic alcohol use in the home was constructed from an item than asked the PCG how often the PCG and the other caregiver disagreed about alcohol or drugs, answers that indicated that disagreement was present were coded as an indication of problematic alcohol use.

The PSID-CDS measures emotional distress using a scale developed and tested in the National Health Interview Study (Kessler et al. 2002). To avoid potential masking of model misfit that may occur when aggregate or "parceled" indicators are used (Bandalos and Finney 2001), this model utilized the six component questions of the scale. These items ask about the frequency of bad feelings over the past 30 days, and the PCG responded on a five-point Likert-type frequency scale. Following the ACEs framework, these variables that measure emotional distress in the household were conceptualized as contributing to household dysfunction.

Four variables were used to model abuse. These variables included positive and negative measures. Three of the variables were measured by PSID-CDS interviewer observations. Physical affection was measured in a continuous way by the interviewer reporting on the number of instances of physical affection that the PCG demonstrated towards the child during the interview. Emotional abuse or affection was indicated by a rating of the caregiver on a continuum of "extremely hostile, cold, harsh to child" to "extremely warm, loving to child" (Hofferth et al. 1997). Emotional abuse or affection was additionally indicated by the caregiver's warmth of tone in speaking to the child. The physical affection, hostility, and warmth scales and procedure was adapted from the home observation for measurement of the environment (HOME) scale (Caldwell and Bradley 1984). Physical aggression towards the child was from the PCG response to an item asking PCGs if they would restrain, hit, or threaten their child in response to the child exhibiting inappropriate behavior. This variable was also adapted from the HOME scale (Caldwell and Bradley 1984).

Table 2.1
ACEs measures from the PSID-CDS

Variable	Latent Variable	Reporter	Scale
Both biological parents in the home	HH	Demographic Variable	Dichotomous
Family hits each other	HH	Primary Caregiver	5-point Likert Scale: Agree
Disagreement about Alcohol Use	HH	Primary Caregiver	Dichotomous
Emotional Distress: Nervous	HH	Primary Caregiver	5-point Likert Scale: Frequency
Emotional Distress: Hopeless	HH	Primary Caregiver	5-point Likert Scale: Frequency
Emotional Distress: Restless	HH	Primary Caregiver	5-point Likert Scale: Frequency
Emotional Distress:	HH	Primary Caregiver	5-point Likert Scale:

Everything an effort			Frequency
Emotional Distress: Sad	HH	Primary Caregiver	5-point Likert Scale: Frequency
Emotional Distress: Worthless	HH	Primary Caregiver	5-point Likert Scale: Frequency
Physical Affection	AB	PSID Interviewer	Continuous
Hostility towards child	AB	PSID Interviewer	5-point Likert: Intensity
Warmth towards child	AB	PSID Interviewer	5-point Likert: Intensity
Physical aggression: hit or threaten child in response to bad behavior†	AB	Primary Caregiver	Dichotomous

Notes: Where HH denotes household dysfunction, and AB notes abuse. † This variable was constructed from three variables that provided the same prompt but are separated by age group in the data set.

Due to the limited nature of the response options, and following the example of existing CFA work in the ACEs field (e.g., Brown et al. 2015; Ford et al. 2014), all indicators other than the measure of physical affection were treated as categorical. When necessary, variables were linearly transformed in order to model greater dysfunction as a higher positive value. This process consisted of reversing the scale for the hostility and warmth variables along with the variables measuring emotional distress. These items employ a five-item Likert scale; the reverse scoring procedure consisted of systematically changing values of 5 to 1, 4 to 2, 2 to 4, and 1 to 5. The neutral response of 3 was left unchanged. To reverse the values for the physical affection variable, which was continuous, response values were subtracted from the maximum value. These transformations were conducted to increase interpretability of the final model, as theory would predict that greater dysfunction on each variable would function in the same direction. Prevalences of positive indication of these ACE variables in the sample are presented in Table 2.2, along with the prevalence in demographic groups. It should be noted that these values are provided for descriptive purposes only, as the CFA utilizes the full range of responses.

Table 2.2
Prevalence of ACEs in sample and subgroups of PSID-CDS in percent.

Variable	Total	Gender		Race		Age Group	
		Male	Female	White	Person of Color	Under 12	12 and Over
Biological Parent	35.0	37.1	32.9	28.8	45.9	33.6	36.1
Family Violence	14.0	14.3	14.0	15.1	11.8	15.5	12.8
Disagree Alcohol	11.2	10.7	11.6	9.9	13.4	10.6	11.7
Nervous	32.7	33.6	31.7	28.9	39.4	30.6	34.6
Hopeless	8.8	9.0	8.8	6.4	13.3	8.0	9.7
Restless	29.9	29.7	30.0	26.3	36.0	30.5	29.3
Effort	28.3	29.0	27.3	22.9	37.7	28.0	28.4
Sad	9.8	8.6	10.9	5.1	17.9	8.9	10.6
Worthless	5.3	4.5	6.2	3.0	9.6	3.6	6.8
Physical Affection	†	†	†	†	†	†	†
Hostile	26.2	24.4	28.0	19.1	25.8	22.4	30.0
Warmth	30.8	30.7	30.9	25.2	41.1	30.2	31.5
Hit or Threaten	0.3	0.4	0.2	0.1	0.7	0.1	0.5
At least 1 ACE	79.5	80.2	78.8	75.3	86.8	79.9	79.2

Notes: Percentages based on weighted data. For multi-categorical variables responses that indicated "some of the time" or greater were aggregated. † indicates a continuous variable which is inappropriate for reduction to a binary indicator.

Grouping Variables. Three variables were constructed in order to define groups to test for invariance. These variables are presented in Table 2.3. The gender variable was available for all respondents and provided a dichotomous split between males and females. The race variable collapsed all groups into a white or person of color binary, in order to maintain group size and provide an interpretable split. The representation of additional racial and demographic groups in the weighted data is limited, hindering more detailed analysis. The age variable was constructed to split the sample at the median age of 12. This yielded groups of equivalent size while separating teenagers from pre-teenagers, as they are frequently studied as different groups.

Table 2.3
Demographic variables for grouping

Variable	N	Percent of total sample
Gender	2907	100
Male	1472	50.6
Female	1435	49.4
Race	2900	99.8
White	1365	47.0
Person of Color	1535	52.8
Age	2907	100
Under 12	1442	49.6
12 and over	1465	50.4

Notes: Counts are for unweighted data.

Missing Data. Statistical methods including multiple imputation and maximum likelihood are generally considered acceptable for data that is missing at the item or scale level (Schafer and Graham 2002). In this study, cases were analyzed for missingness at the scale level (Newman 2009). Those cases missing more than half of responses on ACEs indicators associated with abuse or household dysfunction were regressed on the variables used to balance the PSID-CDS data set (race, census region, urbanicity, and socioeconomic status) and no significant relationships were determined. This subset was retained for further analysis, for a total of N = 2907. The full information maximum likelihood (FIML) algorithm native to MPlus was used to estimate parameters based on the data available for all subsequent analyses (Muthén and Muthén 1998). Auxiliary variables were used in the FIML procedure. Auxiliary variables are correlated with the residual of the indicator variables (Enders 2010; Graham 2003). FIML with auxiliary variables has been shown to yield parameter estimates that are “equally unbiased and efficient” when compared to estimation maximization and multiple imputation approaches (Graham 2003, p. 92). A total of 15 auxiliary variables related to demographic characteristics and childhood assessment scores were used in the estimation procedure.

Analytical Approach

The central analytical approach in this study was confirmatory factor analysis. CFA is a type of structural equation modeling that focuses on the relationships between observed measures and theoretical models (Brown 2015). In this study, CFA was used to evaluate the fit of the theoretical ACES model with the data in the PSID-CDS. Models were tested for goodness of fit based on their ability to recreate the variances and covariances present in the raw data. Nested models were compared based in the comparative increase or decrease in misfit related to the different specifications.

Due to the highly developed nature of the ACEs model as a theoretical framework, an exploratory factor analysis was not conducted in this study. Instead, following the theoretical ACEs model (Felitti et al. 1998; Felitti and Anda 2010), the ACEs indicators were grouped into categories of household dysfunction and abuse. These variables and groupings are shown in Table 2.1. The six items constituting the emotional distress subscale were allowed to covary in order to allow for methodological effects (Brown 2015).

The fit of a measurement model is evaluated based on the ability of the relationships implied by the theoretical model to recreate relationships present in the data. A number of fit statistics and indexes are used to measure fit. As summarized by Brown (2015), these include the root mean square error of approximation (RMSEA), which approximates the extent to which the model fits the population, the comparative fit index (CFI), which evaluates the degree to which the model differs from a baseline model, and the Tucker-Lewis fit index (TLI), which is similar to the CFI but adjusts for the addition of parameters that do not improve the overall fit. The analyses in this study were conducted with MPlus Version 7, using the weighted least squares means and variance adjusted (WLSMV) estimator due to the utilization of categorical indicators, the use of weights, and the capacity of the WLSMV to enable difference testing for more parsimonious models (Muthén and Muthén 1998).

The model was evaluated for parsimony and equality of factor loadings in order to create comparisons to cumulative risk models that are commonly used in ACEs research (Evans et al. 2013). This was tested by comparing the two-factor model with a one-factor model in which all ACE indicators were modeled as loading onto one latent measure of adversity. Difference testing was conducted using the scaled Satorra-Bentler chi-square values. Additionally, difference testing was conducted with models where factor loadings were fixed to a common value in both the one factor and two factor solutions. Due to the use of the WLSMV estimator, a scaled value was used, and difference testing was conducted using the function native to MPlus (Muthén and Muthén 1998).

The two-factor model was further evaluated for invariance across demographic groups. Previous research involving ACEs has indicated the potential for differences across gender (Evans et al. 2008), race (Bethell et al. 2014) and age (Flaherty et al. 2013). In light of these findings, the model was evaluated for consistency across demographic groups. Models were evaluated for invariance of the variance-covariance matrix across groups, (Satorra and Rivera 2012; Vandenberg and Lance 2000), configural invariance, or “weak factorial invariance” (Horn and McArdle 1992), which specifies the same pattern of variable relationships across the groups, and “metric invariance” (Horn and

McArdle 1992) which constrains the factor loadings to be equal across groups. These nested tests are necessary for the establishment of group invariance (Satorra and Rivera 2012; Vandenberg and Lance 2000).

Results

Confirmatory factor analysis

The structure of the ACEs two-factor model is presented in Figure 2.1, which shows the organization of the indicators onto the factor model and standardized factor loadings. The model is over-identified, with 49 degrees of freedom. The RMSEA value of this model was 0.021, below the cutoff of 0.05 that denotes an excellent fit (Hu and Bentler 1999). The 90% confidence interval for the RMSEA value was 0.015 – 0.026. The CFI value for the model was 0.993 and the TLI value was 0.989, both above the cutoff of 0.95, denoting excellent fit (Hu and Bentler 1999). These values indicate that the relationships implied in the theoretical model reproduce the variance-covariance matrix present in the sample data.

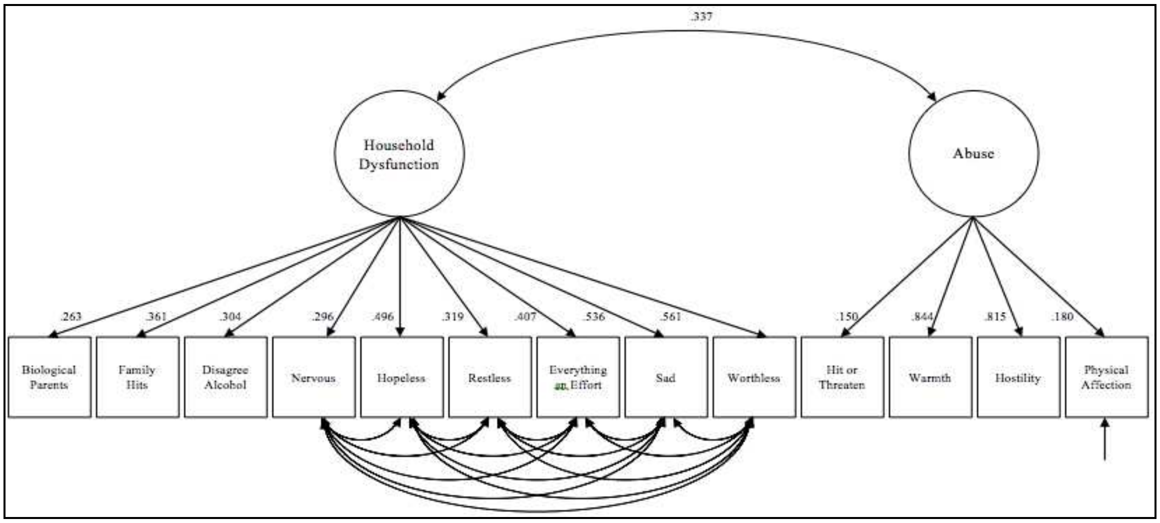

Figure 2.1: Two-factor measurement model for ACEs. Latent factors represented with circles; direct indicators represented with squares. Factor loadings shown as one-headed arrows from latent factors to indicators. Residual covariances shown as two-headed arrows connecting indicators. Residual errors shown as a one-headed arrow on indicators; residual error is only present for continuous indicators. Factor covariances shown as two-headed arrow connecting latent factors. All values standardized.

Standardized factor loadings can be interpreted as the correlation between the indicator and the latent factor (Brown 2015). The standardized factor loadings and their related statistical significance for this model are presented in Table 2.4. All of the indicators loaded in the direction predicted by theory; i.e., loadings were positive for all indicators. Factor loadings that are statistically significant at the $p < .01$ level and greater than $\lambda = 0.3$ can be considered salient factor loadings (Brown 2015). The loadings for the indicators of abuse vary from high and statistically significant (hostility and warmth) to marginal but significant (physical affection) to marginal and not statistically significant (hit or threaten). The loadings for the indicators of household dysfunction are all statistically significant, while relatively low in value, including the indicator of both parents in the household and primary caregiver nervousness, which are less than the cutoff point of $\lambda > 0.3$ for salient factors.

Table 2.4
Standardized factor loadings, standard errors, and communalities from two-factor model

Latent Variable	Indicator	Factor Loading	Standard Error	Communality	Standard Error
HH	Biological Parent	.265**	.056	.070*	.029
	Family Violence	.361**	.063	.131*	.046
	Disagree Alcohol	.304**	.068	.093*	.041
	Nervous	.296**	.063	.088**	.037
	Hopeless	.496**	.080	.246**	.080
	Restless	.319**	.065	.102*	.041
	Effort	.407**	.069	.166**	.056
	Sad	.536**	.082	.288**	.088
	Worthless	.561**	.097	.315**	.109
AB	Physical Affection	.180**	.029	.033**	.011
	Hostile	.815**	.055	.663**	.089
	Warmth	.844**	.057	.713**	.096
	Hit or Threaten	.150	.186	.023	.056

Notes: Where HH denotes household dysfunction, and AB notes abuse. * denotes $p < .05$, ** denotes $p < .01$.

Squaring the standardized factor loadings yields communality values. This value can be interpreted as the portion of the variance in the indicator accounted for by the latent variable (Brown 2015). Table 2.4 presents communality values. Communality values for the indicators range from relatively high, such as the hostility and warmth indicators, to relatively low, with the values for indicators associated with biological parents, primary caregiver nervousness, disagreement over alcohol use, physical affection, and physical aggression all below 10%, and the physical aggression indicator community failing to reach statistical significance at the $p < .05$ level.

Results from this analysis indicate that whereas the overall two-factor model provides an excellent fit for the data, some of the individual indicators are correlated with their latent factors at a low level. Additionally, the values of communality indicate that some of the indicators are only marginally related to their latent dimensions (Brown 2015). Finally, the latent factors of household dysfunction and abuse are correlated at a moderate level ($r = 0.337$, $p < 0.01$). This indicates that the ACEs theoretical model, operationalized in the two latent factor model, reproduces the relationships between indicators observed in the data, while not fully relating all of the indicators to the ACEs constructs.

The removal of individual indicators from the model generates non-nested models that, given the employment of the WLSMV estimator, are not directly empirically comparable (Brown 2015). However, to identify the increase in model misfit associated with isolating indicators from latent factors, factor loadings of individual indicators were systematically fixed to zero and the resulting models compared to the full two-factor model using difference testing. Results from this procedure indicated that restricting factor loadings to zero significantly increased the misfit in the model with the exception of the indicator of physical aggression ($\chi^2 = .641$ $df = 1$, $p > .05$). This was likely due to the low signal in the indicator. According to Brown (2015), such a scenario "does not substantially degrade the fit of the model (assuming that the model is well specified otherwise)" (p. 156). Due to alignment with the theoretical framework, and the excellent model fit with all indicators included, the full compliment of indicators was retained for additional testing.

One factor structure comparison

Cumulative risk models of ACEs collect all ACE indicators into one measure (Evans et al. 2013). However, ACEs research is founded on separate categories of adverse experiences, and authors commonly maintain these categories in discussion

(Felitti et al. 1998; Felitti and Anda 2010; Guinosso et al. 2016). The initial analysis of the measurement model in this paper indicates a relationship between the household dysfunction and abuse latent variables of ACEs. These theoretical and empirical observations necessitate a comparison of a more parsimonious one-factor solution.

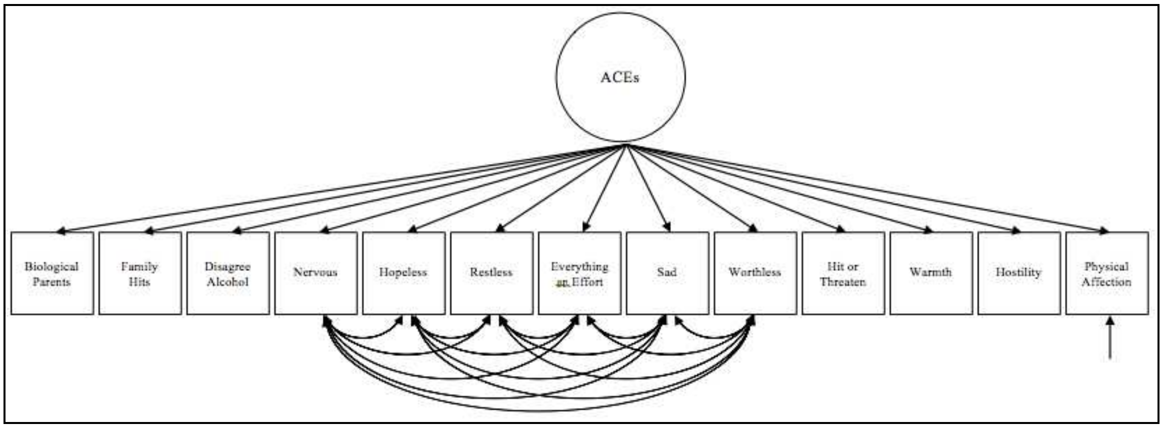

Figure 2.2: One-factor model for ACEs. Latent factors represented with circles; direct indicators represented with squares. Factor loadings shown as one-headed arrows from latent factors to indicators. Residual covariances shown as two-headed arrows connecting indicators. Residual errors shown as a one-headed arrow on indicators; residual error is only present for continuous indicators.

A one-factor model was constructed with all indicators loading onto one factor. This model is shown in Figure 2.2. The fit of this model was compared to the fit of the two-factor model using difference testing. The one-factor model represented a significant increase in misfit for the data when compared with the original two-factor model (χ^2 = 55.828, $df = 1$, $p < .001$). This result leads to a rejection of the null hypothesis that the one-factor model does not increase misfit. Although fit statistics for this one-factor model indicate excellent fit (RMSEA = 0.032, 90% RMSEA CI: 0.028 – 0.037, CFI = .983, TLI = .974), this approach both ignores the theoretical categorization of ACEs and is empirically shown to be a poorer fit for the data when compared with the theoretically-aligned two-factor model. For theoretical and empirical reasons, the two factor ACE model was retained.

Equality of factor loadings

Cumulative risk models constrain all individual ACEs indicators to having the same weight in determining the value of the overall ACEs indicators (Evans et al. 2013). In order to test this assumption, models were constructed wherein the factor loadings were constrained to equality. Using the two-factor model, all loadings for indicator variables across the two latent factors were constrained and the result compared to the original two-factor model where loadings were allowed to freely vary. This test resulted in a significant increase in misfit for the data (χ^2 = 578.382, *df* = 12, $p < .001$). A weaker assumption, that loadings should be invariant within the individual categories but allowed to be different across the categories of ACEs, was also tested. Loadings for the abuse indicator variables were constrained to equality and loadings of the household dysfunction latent factor were constrained to equality but allowed to be different than the abuse indicator loadings. This test also resulted in a significant increase in misfit for the data when compared to the original two-factor model (χ^2 = 40.728, *df* = 11, $p < .001$).

In order to fully investigate the cumulative risk model, the one factor solution was also tested in this manner. Starting with the one factor solution in Figure 2.2, all factor loadings were fixed to be equal to each other. The results from this test indicated that such a constraint significantly increased the model misfit for the data when compared with the one factor solution wherein all loadings were allowed to freely vary (χ^2 = 657.195, *df* = 12, $p < .001$). The results from these tests indicate that, contrary to how they are treated in cumulative risk models, ACEs indicators do not equally relate to the ACEs construct.

Group invariance

To observe if the model is appropriate for applications that utilize gender groups, the two factor solution was tested for invariance across genders. As proscribed by Vandenberg and Lance (2000), the procedure can be conducted in a step-wise manner. The first step in such invariance testing is an omnibus test that compares the variance-covariance values across the groups. The null hypothesis for this test is that the variance-covariance matrix is the same for the two groups. The value of the test of model fit indicates that this hypothesis cannot be rejected ($\chi^2 = 76.967$, $df = 67$, $p > .05$; RMSEA = 0.010, 90% RMSEA CI: 0.000 – 0.019, CFI = 0.999, TLI = 0.999). The second step tests for configural invariance across the different groups. This procedure specifies the same structure for the two groups but does not constrain parameters to equality across the models. Results from this model show excellent fit (RMSEA = 0.023, 90% RMSEA CI: 0.018 – 0.028, CFI = 0.994, TLI = 0.992). This indicates that the model structure is suitable for both male and female groups.

The next step tests for metric invariance by fixing the values of the parameters across the two models. The results from this test indicated that constraining the values of factor loadings across the two groups did not result in a significant increase in misfit when compared to the baseline model ($\chi^2 = 37.5210$, $df = 28$, $p > .05$). Due to the utilization of categorical variables in the measurement model, tests related to the invariance of residuals require fixing the number of thresholds for each categorical variable and fixing the value of the residual variance to 1 (Muthén and Muthén 1998).

The means and variances for the continuous variables were also fixed across groups at this step. Comparison to the baseline model indicated no significant increase in misfit (χ^2 = 50.832, *df* = 42, *p* > .05). Finally, the covariance between the latent factors was fixed, yielding no significant increase in misfit from the baseline model (χ^2 = 54.212, *df* = 43, *p* > .05). The demonstrated group invariance indicates that the gender groups are comparable within this model (Vandenberg and Lance 2000).

In a similar way, group invariance was also tested for groups separated by race and age. For race, white participants were compared to people of color. For age, a cut point of 12 years old was selected to evenly divide the total sample. In both cases, the models were unable to be compared due to a lack of variance in the data within these smaller groups. Specifically, the indicators of hostility and physical aggression did not demonstrate the variance necessary to measure covariance with other variables, meaning that the variance-covariance matrices could not be constructed and compared. When divided into these smaller groups, some response categories contained no individuals, and these empty categories were different across the groups. These results indicate that group-level analyses with regard to race and age cannot be made based on this model.

Discussion

The ACEs framework has been used in numerous studies as a predictor of negative outcomes in adulthood (Felitti and Anda 2010). These studies consistently employ a cumulative risk approach to modeling ACEs, wherein individual variables are mapped onto binary indicators, and then summed to generate an indicator of ACEs suitable for inclusion in regression (Evans et al. 2013). Such an approach restricts the modeling of indicators in three important ways. First, it restricts each indicator as having the same impact as every other indicator. Second, it disregards the intensity or level of each individual ACE, limiting each to an indicator of presence or absence. Third, it groups the indicators into one category, rather than separate but correlated categories. This study demonstrates challenges to this practice.

Results indicate that the individual measures of ACEs differentially contributed to the overall measure of the ACEs. Factor loadings varied greatly, with numerous indicators loading at a marginal level ($\lambda < 0.3$). When loadings were constrained to equality, model misfit significantly increased. The wide range of commonality values further supports this conclusion, as the relationship between the indicators and the latent variables was widely varied. Although some researchers have utilized weighting procedures to differentiate the impact of individual ACEs on the total ACE indicator, these models do not outperform unweighted models and are often unstable over time (Evans et al. 2013; Flouri 2008). Results from this analysis demonstrate the potential for latent factor procedures to address this issue of differential influence while bypassing the difficulties incurred in weighted regression procedures.

The increase in misfit when loadings were constrained, along with the overall fit of the two-factor model, opposes the common practice of using a summation of presence/absence indicators of ACEs (e.g., Björkenstam et al. 2015; Dong et al. 2004; Felitti et al. 1998; Felitti and Anda 2010). Such practices rely on the imposition of cut points by researchers, or providing only dichotomous options to survey participants, a practice that has previously been identified as a shortcoming in ACEs research (Evans et al. 2013). The results from this study support the work of other researchers (e.g., Brown et al. 2015; Ford et al. 2014) that demonstrate latent factor approaches, which retain the variability within indicators, can be used when modeling ACEs.

The results from the parsimony analyses further call into question the practice of collecting all ACE indicators into one cumulative risk variable. The significant increase in model misfit that occurred when gathering all indicators onto one factor points to the misspecification introduced by the practice. Although composite ACE variables are both parsimonious and easily interpreted (Evans et al. 2013), results from this study show that this practice may collapse conceptually distinct measures into the same variable. Conceptually, the ACE framework makes these distinctions; however, in application such distinctions are frequently disregarded. Results from this study support the retention of such distinctions.

The differences in the variance-covariance matrices across race and age groups further point to the necessity for more refined methods in measuring ACEs. As noted elsewhere (Bethell et al. 2014; Flaherty et al. 2013), ACEs may function differently across demographic groups. The utilization of omnibus measures across distinct groups can serve to mask the differential effects of adversity and lead to unwarranted conclusions being applied to groups were adversity functions in a different way (Garcia Coll et al. 1996). The results from this study further caution against utilization of ACEs measurement models without investigating invariance across demographic groups.

The results from this study also indicate that the PSID-CDS is a useful data set for future research using the ACEs framework. As previously demonstrated by Björkenstam and colleagues (2015), indicators from the PSID-CDS can be mapped onto the ACEs framework. However, unlike that study, this work identifies indicators that closely parallel the original ACEs framework, allowing for interpretation in relation to the existing body of literature. The PSID-CDS provides a rich palette of variables aligned with the ACEs framework, along with a sample large enough to allow for full model identification. The results from this study indicate the utility of a latent factor approach to modeling PSID-CDS data, rather than previous studies using the PSID-CDS, which employed a cumulative risk model (e.g., Björkenstam et al. 2015; Ciula and Skinner 2015). Additionally, results from the tests for group invariance indicate that this model functions in the same way across gender lines, making it a useful tool in investigating the differential effects of additional exogenous variables along with ACEs on outcomes of interest.

The data in this study include self-reports from parents on variables of household dysfunction. In their study employing the PSID-CDS to demonstrate links between parenting and achievement, Tang and Davis-Kean (2015) point out that under-reporting parenting behaviors would result in more conservative estimates of the effect of these parenting processes. Additional studies using these parental indictors similarly note this limitation, and the potential to provide conservative estimates (e.g. Yang and McLoyd 2015). As this study employed responses from parents, the estimates of the frequencies of ACEs indicated by parents may be conservative. Research utilizing retrospective data from PSID-CDS children could provide additional perspective on the findings of this research.

Adverse childhood experiences occur at far-too-frequent of a rate in the United States. The ACEs framework provides a common way for researchers in different fields using different data sources around the globe to identify adversity and collaborate in investigating relationships of ACEs to outcomes. This study demonstrates that the data in the PSID-CDS can be used with a latent factor approach to allow for the full variance present in the data to be incorporated into a model of ACEs. This study furthers our understanding of the ACEs model, demonstrating that the constructs, when treated as a collection of binary indicators, may not provide an appropriately detailed portrait of ACEs. By adding more nuanced approaches into the conversation, this study can support advocates for children as they seek to influence policymakers in the crafting of supports for these children, to better their lives and the larger society in which we all live and grow.

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CHAPTER 3

Childhood Adversity, Families, Neighborhoods, and Cognitive Outcomes: Structural Models of the Bioecological Framework

Introduction

The bioecological model of development posits that children develop through interactions with individuals, groups, and structures within their proximal and distal contexts (Bronfenbrenner, 1994; Bronfenbrenner & Morris, 2006). To better understand how a child develops, it is necessary to understand and analyze the context in which the child experiences development, as such contexts have direct and indirect effects (Bronfenbrenner, 1979). This bioecological perspective is used by the World Health organization (Blas & Kurup, 2010) and the US Department of Health and Human Services (2010) to conceptualize various phenomena and conduct research related to human development and public health. In order to understand child development, it is vital to understand the context within which such development occurs.

Two such proximal contexts are the family environment and the childhood neighborhood (Berns, 2010). Families and neighborhoods have been shown to be linked to both cognitive and socioemotional outcomes in children (Burdick-Will et al., 2011; Cicchetti, 2013; Fowler, Tompsett, Braciszewski, Jacques-Tiura, & Baltes, 2009; Repetti, Taylor, & Seeman, 2002). Families can be conceptualized as having both supportive and deleterious influences on development (S. E. Evans, Davies, & DiLillo, 2008; Hill & Tyson, 2009). Similarly, characteristics of neighborhoods have been shown to have positive and negative influences on developmental outcomes (Leventhal & Brooks-Gunn, 2000; Sharkey & Faber, 2014). While researchers have posited a number of routes or mechanisms for these influences, their existence is well-accepted (Finkelhor, Shattuck, Turner, & Hamby, 2015; Sharkey & Faber, 2014).

Developmental science contains multiple models of human growth, including personal change, contextual, regulation, and representational (Sameroff, 2010, p. 12). This study is situated within the contextual growth model, and focuses on families and neighborhoods as proximal systems with which the individual interacts and consequentially experience development. The interactions between children and these contexts change over time, as both they and the contexts continue to grow and change. In order to contribute to understanding of development, rather than parsing out the individual effects of contexts and situations, theoretical constructs measuring dimensions of these constructs can be used (Sameroff, 2010, pp. 13–14). This study uses cross-sectional data from children ages 5-17 to measure constructs of individual adversity as designated by the Adverse Childhood Experiences (ACEs) framework, family conflict, and neighborhood quality, and models the relationships of these constructs with cognitive outcomes. A bioecological framework of development was used to guide the structure of these models and to provide an analytical framework for interpretation of the results.

Theoretical Frameworks

Bioecological model of human development

Human development can be conceptualized as "the person's evolving conception of the ecological environment, and his relation to it, as well as the person's growing capacity to discover, sustain, or alter its properties." (Bronfenbrenner, 1996, p. 9) The bioecological model of human development (Bronfenbrenner, 1976, 1986; Bronfenbrenner & Morris, 2006) expanded on previous models of development by broadening and elevating the role of context. This model recognizes that the individual develops through “progressively more complex reciprocal interaction between an active, evolving bio-psychological human organism and the persons, objects, and symbols in its immediate external environment” (Bronfenbrenner & Morris, 1998, p. 996). These “proximal processes” occur over extended periods of time and may contribute to competence or dysfunction (Bronfenbrenner & Morris, 1998).

In the bioecological framework, a microsystem is a contextual element with which the individual directly interacts (Berns, 2010; Bronfenbrenner, 1976). The microsystem and the individual influence each other through these interactions. The family can be considered to be a microsystem, as the developing individual interacts directly with the family and its dynamics (Bronfenbrenner, 1986). Similarly, the neighborhood, including individuals and institutions, is a microsystem (Berns, 2010; Bronfenbrenner, 1994). Developmental contexts in bioecological theory expand outward from this micro level to include mesosystems, or interactions between microsystems; exosystems, or interactions between microsystems and larger systems; and macrosystems, or the larger social or cultural contexts within which individual development takes place.

Although Bronfenbrenner’s nomenclature of these systems is not universally accepted, the conceptual framework is widely used to guide research within the contextual model of development (Sameroff, 2010). Studies that employ the bioecological model necessarily investigate the structures that impact development in their naturally occurring context, rather then an artificial environment, in order to maintain the ecological integrity of the study (Bronfenbrenner, 1994)). This edict intimates the utilization of existing measures of the individual and developmental contexts.

Adverse Childhood Experiences

The Adverse Childhood Experiences (ACEs) framework is a conceptualization of adversity that is widely used in the social sciences and public health (Center for Disease Control and Prevention, 2015; Felitti et al., 1998; Larkin, Felitti, & Anda, 2014; McLaughlin, Sheridan, & Lambert, 2014). Originally constructed by Felitti and colleagues (1998), the ACEs framework has been used to link childhood experiences with deleterious repercussions in adulthood. The framework categorizes adverse experiences into abuse, neglect, and household dysfunction (Felitti et al., 1998; Felitti & Anda, 2010). Although conceptually distinct, such experiences were found to rarely occur in isolation (Dong et al., 2004). ACEs have been shown to be correlated with adult outcomes such as smoking (Anda et al., 1999), drug use (Dube et al., 2003), sexually transmitted disease (Hillis, Anda, Felitti, Nordenberg, & Marchbanks, 2000) risk of suicide (Dube et al., 2001), and overall personal health (Felitti et al., 1998).

The negative impact of ACEs is measurable during childhood and adolescence. Similar to studies of adults, teens who report adverse experiences are more likely to experience depression, drug abuse, and antisocial behavior in young adulthood (Schilling, Aseltine, & Gore, 2007). In addition to health outcomes, children who were reported to have experienced multiple ACEs were more likely to have issues with behavior and developmental tasks (Marie-Mitchell & O’Connor, 2013). These individuals have also been shown to have lower rates of engagement at school (Bethell, Newacheck, Hawes, & Halfon, 2014). The persistent occurrence of ACEs has greater negative effects on IQ and behavior than limited occurrences (Jaffee & Maikovich-Fong, 2011). The multidimensional nature of adversity and its connections to other contextual elements are apparent early in a child's life (Hindman, Skibbe, Miller, & Zimmerman, 2010).

Although ACEs measurement is generally conducted through a cumulative risk model (G. W. Evans, Li, & Whipple, 2013), wherein individual ACEs are collapsed to a presence/absence indicator, and the indicators summed to produce a composite score, recent innovations in the ACEs field have called this practice into question (G. W. Evans et al., 2013; Ford et al., 2014; Guinosso, Johnson, & Riley, 2016; Olofson, 2017). The cumulative risk practice constrains individual ACEs to equivalent influence on the outcomes while collapsing the variability within the individual indicators (G. W. Evans et al., 2013). A latent factor approach can be used to maintain the variability in the indicators and allow for differential contributions by the indicators to the ACEs measure (G. W. Evans et al., 2013; Ford et al., 2014). This approach also allows for structural equation modeling methodology to be used to incorporate latent measures of developmental contexts aligned with the bioecological model of development.

Family Conflict

"The maltreating home represents such a dramatic violation of the average expectable environment, research on child maltreatment informs developmental theory by elucidating the conditions necessary for normal development and healthy adaptation" (Cicchetti, 2013, p. 2). The family environment has be conceptualized as a microsystem influencing development when viewed through a bioecological lens (Berns, 2010; Repetti et al., 2002). Families can shape the cognitive development of the child through both the support that is provided and the conflict that is present in the home (S. E. Evans et al., 2008; Hill & Tyson, 2009). Family conflict can be modeled on a continuum from physical violence (e.g., S. E. Evans et al., 2008) to relational hostilities (e.g. Forehand, Biggar, & Kotchick, 1998). This approach to modeling family conflict has been used in large scale national studies (Sweet, Bumpass, & Call, 1988). The model of family conflict used in this study is based on questions asked of a caregiver about the family unit. Although the individual is exposed to the conflict, the family conflict is considered contextual as related to the individual as measured by the ACEs framework.

Family conflict has been found to be predictive of later in life metal health outcomes (Herrenkohl, Kosterman, Hawkins, & Mason, 2009; Paradis et al., 2009), risky sexual behavior (Lyerly & Brunner Huber, 2013), and substance abuse issues (Herrenkohl, Lee, Kosterman, & Hawkins, 2012). The effects of familial conflict can be manifested much earlier, including in early adolescence (S. E. Evans et al., 2008). Children exposed to familial conflict experience negative impacts on educational outcomes in both the short and long term (Forehand et al., 1998). Children exposed to conflict or violence in the home express higher incidence of negative socioemotional outcomes (S. E. Evans et al., 2008; Sheeber, Hops, Alpert, Davis, & Andrews, 1997). Clarkson Freeman (2014) found that children from families with high levels of conflict, aggression, or hostility have an increased risk for internalizing and externalizing behaviors, poor social skills, and difficulty processing their emotions. However, these families do not exist in isolation, and the interplay between families and their neighborhood contexts is complex and mixed (Briggs, Popkin, & Goering, 2010).

Neighborhood Quality

Neighborhoods have been conceptualized as the people, physical space, social service catchment space, or institutions that connect to or segregate them from each other (Entwisle, 2007). The mechanisms through which neighborhoods cause a developmental effect on the individual can be categorized in a number of different ways. In their seminal review of neighborhood effects literature in the 1960s, 70s, and 80s, Jencks and Mayer (1990) identified epidemic models, which focused on the influence of peers; institutional models, which focused on the role of adults outside the neighborhood; and collective socialization, which emphasized the role of adults in the neighborhood. Leventhal and Brooks-Gunn (2000) further developed these categories of neighborhood-level mediators, conceptualizing institutional resources, interpersonal relationships, and neighborhood norms as vital dimensions. Elaboration of these categories position neighborhood cohesion, interpersonal interactions, and the collective social norms as elements of a larger social interaction mechanism that operationalizes neighborhood effects (Galster, 2012). The presence of neighborhood violence and safety is generally conceptualized as a separate but vital element of neighborhoods that has an impact on children (Fowler et al., 2009; Galster, 2012). This study utilizes the concepts of neighborhood cohesion, collective norms, and safety to create a measurement of overall neighborhood quality. Both social interaction mechanisms such as cohesion and collective norms and environmental mechanisms such as safety have been shown to have development impacts (Brooks-Gunn, Duncan, Klebanov, & Sealand, 1993; Burdick-Will et al., 2011; Fowler et al., 2009).

Academic outcomes can be used to measure the long-term effects of neighborhoods (G. J. Duncan & Magnuson, 2011). Brooks-Gunn and colleagues (1993) found that the presence or absence of positive influences in the neighborhood, rather than the presence of negative influences affected children's test scores. Although school quality and neighborhood quality are intertwined with regard to academic outcomes (Dobbie & Fryer Jr, 2011), neighborhoods have been shown to have an effect on cognitive outcomes independent from schools (Burdick-Will et al., 2011). However, as argued by Sharkey and Faber (2014), neighborhood effects should not be considered in isolation.

Purpose of this study

Developmental science, particularly that which operationalizes a bioecological model, remains in relatively early development (Bronfenbrenner & Morris, 2006). Empirical studies utilizing the framework can advance this science "by seeking and obtaining empirical findings that might call into question relationships posited in the existing theoretical model" (Bronfenbrenner & Evans, 2000, p. 116). The purpose of this paper is to investigate the relationships among ACEs, family conflict, and neighborhood quality on cognitive outcomes through the lens of a bioecological model of development. With respect to the individual, families and neighborhoods can be considered microsystems. When modeled independently, children with more occurrences of ACEs and conflict in the family have been shown to have worse cognitive outcomes than children with fewer occurrences of ACEs and conflict, while quality neighborhoods have been shown to be positively predictive of cognitive outcomes. However, rather than family conflict and neighborhood quality directly influencing cognitive outcomes, the bioecological model posits that these contexts should be modeled as acting through their influence on the individual. This study seeks empirical evidence for this interpretation.

According to Bronfenbrenner & Morris (2006), bioecological development research that occurs in "discovery mode" is theoretically driven and should increase in complexity, with the theoretical implications serving as vital outcomes. In this study, increasingly complex interactions among the three variables of interest were tested. First, the individual constructs were tested for fit and relationship to the outcome variables of interest. Following these foundational analyses, structural models were constructed to test the viability of direct and indirect paths from the microsystems of families and neighborhoods through the individual to cognitive outcomes. These two stages, then, address two different research questions:

1) When modeled using ACEs, family conflict, and neighborhood quality, what is the nature of the path coefficients from the individual, families, and neighborhoods to cognitive outcomes?
2) Are the relationships between the family and neighborhood contexts and cognitive outcomes better modeled as a direct pathway or as indirect pathways through the individual as measured by ACEs, consistent with the bioecological model of development?

Methods

Instrument

The data for this study was taken from the Panel Study of Income Dynamics Child Development Supplement (PSID-CDS). The larger Panel Study of Income Dynamics (PSID) collects information about the economic and life course development of families in the United States (McGonagle, Schoeni, Sastry, & Freedman, 2012). Since its inception in 1968, the PSID has collected data on a nationally representative sample of families, and has followed the offspring of those families, subsequently increasing in size and scope. In 1997 the PSID-CDS was launched with a subset of PSID families in order to better understand the lives of children. The PSID-CDS drew from existing surveys for items measuring constructs of interest; new and revised items were included as well. The data set contains over 500 indicators collected from children, parents, teachers, and other caregivers (Hofferth, Davis-Kean, Davis, & Finkelstein, 1997). Although frequently used in the field of economics, this data set is beginning to be utilized by researchers investigating childhood adversity and development (e.g., Björkenstam et al., 2015; Ciula & Skinner, 2015; Olofson, 2017).

Sample

At its launch in 1997, the PSID-CDS identified 2705 families in the PSID core sample with children ages 12 and younger for further data collection (Hofferth et al., 1997). In this initial 1997 wave, data was collected on 3653 children ages 0-12. The PSID-CDS was collected again with subsequent waves in 2002 and 2007. Attrition rates over the three waves were low and in alignment with other, similar studies (Institute for Social Research, 2010). Data from the 2002 wave was used in this study to maximize the sample size of children with some life experience. In 2002, data was collected on 2907 children ages 5-17. By using weights associated with the data, the sample can be considered nationally representative (Duffy & Sastry, 2012). Following the PSID-CDS technical documents, the primary caregiver/child weight was used in this analysis, which balances the sample on race, geographic location, urbanicity, and level of education of the head of household (Gouskova, 2001). Summaries of demographic characteristics of the weighted sample used in this study are presented in Table 3.1.

Table 3.1
Demographic characteristics of PSID-CDS 2002 sample

Category	Classification	Percent of Sample
<u>*Gender*</u>	Male	49.6
	Female	50.4
<u>*Race*</u>	Person of Color	36.2
	White	63.8
<u>*Census Region*</u>	Northeast	17.9
	North Central	24.4
	South	31.8
	West	25.9
<u>*Urbanicity*</u>	Metropolitan Statistical Area	63.8
	Non-Metropolitan Statistical Area	36.2
<u>*Head Education Level*</u>	Did not graduate high school	19.5
	Graduated high school	80.5

Note: Percentages based on weighted data.

Variables

In this study, individual adversity was modeled using the ACEs framework, families were modeled using indicators of physical and relational conflict, and neighborhoods were modeled with elements of cohesion, collective norms, and safety. These dimensions of the developmental contexts were chosen due to the necessity in bioecological research to provide descriptions of the ways in which the contexts and individual might interact, rather than simply as descriptors of the environments (Bronfenbrenner & Morris, 2006). ACEs, family conflict, and neighborhood quality were modeled as separate latent variables. A latent variable is a variable that is indirectly observed through the sample values of observed variables (Bollen, 2002). The variables used as indicators from the PSID-CDS for the latent variables are described in Table 3.2. The variables used to measure ACEs are aligned with the original ACEs framework (Felitti et al., 1998; Felitti & Anda, 2010). This measure has previously demonstrated to provide an excellent fit for this data using a CFA approach (see Olofson [2017] for a full discussion of this model). To aid in interpretability, a simplified one-factor model of ACEs was used in this study. The measures of family conflict originated in the National Survey of Families and Households (Institute for Social Research, 2010). These items examine methods of conflict resolution within families. The measure of neighborhood quality consisted of eight items that originated in National Longitudinal Study of Youth, the Denver Youth Study and the Project on Human Development in Chicago Neighborhoods (Institute for Social Research, 2010). Except where noted, all indicator variables were collected from the child's primary caregiver. As indicated, when appropriate, variables were reverse-scored in order to maintain coherent directionality across the latent variable. Due to the limited range of response options, all variables were treated as categorical in modeling except where otherwise noted.

Table 3.2
ACEs measures from the PSID-CDS

Latent Variable	Variable	N*	Scale
Adverse Childhood Experiences (ACEs)	Both biological parents present[a]	2891	Dichotomous
	Disagreement about alcohol use	2893	Dichotomous
	Primary Caregiver: nervous	2897	5-point Likert Scale: Frequency
	Primary Caregiver: hopeless	2895	5-point Likert Scale: Frequency
	Primary Caregiver: restless	2895	5-point Likert Scale: Frequency
	Primary Caregiver: everything an effort	2892	5-point Likert Scale: Frequency
	Primary Caregiver: sad	2895	5-point Likert Scale: Frequency
	Primary Caregiver: worthless	2895	5-point Likert Scale: Frequency
	Physical affection[b]	2734	Continuous
	Hostility towards child[c]	2369	5-point Likert: Intensity
	Warmth towards child[b,c]	2369	5-point Likert: Intensity
	Hit or threaten child in response to bad behavior[d]	2784	Dichotomous
Family Dysfunction (FAM)	Family fights a lot	2215	5-point Likert Scale: Agree
	Family throws things	2215	5-point Likert Scale: Agree
	Family calmly discusses problems[b]	2213	5-point Likert Scale: Agree

	Family criticizes each other	2215	5-point Likert Scale: Agree
	Family hits each other	2215	5-point Likert Scale: Agree
Neighbor-hood Quality (NHOOD)	Length of residence[b]	2898	4 category: Length of stay
	Place to raise kids	2897	5-point Likert Scale: Rating
	Difficulty identifying strangers	2893	3-point Likert Scale: Difficulty
	Neighbor report: selling drugs	2876	4-point Likert Scale: Likelihood
	Neighbor report: kids in trouble	2882	4-point Likert Scale: Likelihood
	Neighbor report: disrespectful child	2869	4-point Likert Scale: Likelihood
	Neighbor report: child stealing	2873	4-point Likert Scale: Likelihood
	Safe to walk around after dark	2894	4-point Likert Scale: safety

Notes: * All N values from weighted data. Values rounded to nearest whole person for interpretability. [a] Collected from demographic information. [b] Score reversed for conceptual coherence. [c] Reported by the PSID staff member who completed a home interview with the primary caregiver. [d] Constructed from three variables that provided the same prompt but are separated by age group in the data set.

Three childhood assessments were used to construct the cognitive outcome latent variable. As presented in Table 3.3, these indicators included tests of reading, mathematics, and memory. Age-standardized broad reading and applied problems scores from the Woodcock-Johnson Psycho-Educational Battery-Revised were used (Woodcock & Johnson, 1989). Along with reading and math, scores from the Wechsler Intelligence Scale for Children (WISC) - Revised Digit Span Test for Short Term Memory (Wechsler, 1974) were used. These indicators represent the full complement of cognitive outcome assessments available in the 2002 wave of the PSID-CDS (Institute for Social Research, 2010).

Table 3.3
Cognitive outcome variables

Test	N	Mean	Standard Deviation
Woodcock Johnson: Applied Problems	2625	104.66	17.308
Woodcock Johnson: Broad Reading	2537	105.90	17.605
WISC: Digit Span	2623	14.75	4.562

Note: All values based on weighted data.

Variables of socioeconomic status (SES), gender, and race were constructed for use as controls in path models. The race variable collapsed all groups into a white or person of color binary, in order to maintain group size, provide an interpretable split, and due to similarities in achievement gaps between whites and different communities of color (Todd & Wolpin, 2007). The gender variable was dichotomous indicating non-overlapping groups of males and females, as present in the data set. Following the framework set out by Duncan, Featherman, and Duncan (1972), the SES variable was a composite variable consisting of total household income, highest educational level achieved by the head of the household, and head of household occupational prestige (Hauser & Warren, 1996). A scale score was constructed by standardizing the three continuous variables and summing the standardized values to generate the SES control variable.

Missing Data

Cases were analyzed for missing data at the scale level (Newman, 2009). Missing data for the indicators associated with the latent variables were identified, and those cases missing more than half of the indicators on any one of the latent variables were regressed on the variables used to balance the PSID-CDS data set (Gouskova, 2001); no significant relationships were determined. All cases were retained for further analysis using maximum likelihood estimation, as maximum likelihood is generally considered acceptable for data that is missing at the item or scale level (Schafer & Graham, 2002), and maximum likelihood procedures are favored when using structural equation modeling (Enders, 2010). The full information maximum likelihood (FIML) algorithm native to MPlus was used to estimate parameters based on the data available for all subsequent analyses (Muthén & Muthén, 1998). Auxiliary variables were used in the FIML procedure. Auxiliary variables are correlated with the residual of the indicator variables that are not used elsewhere in the analysis (Enders, 2010; Graham, 2003). FIML with auxiliary variables has been shown to yield parameter estimates that are "equally unbiased and efficient" when compared to estimation maximization and multiple imputation approaches (Graham, 2003, p. 92). A total of 8 auxiliary variables measuring head of household demographic characteristics and child behavior were used in the estimation procedure.

Analysis

The analyses consisted of two stages: confirmatory factor analysis (CFA) and structural equation modeling (SEM). In the first stage, the latent variables representing ACEs, families, and neighborhoods were constructed and assessed for their ability to recreate relationships present in the data. The ACEs factor contained 12 indicators aligned with the ACEs theoretical framework (Felitti et al., 1998; Felitti & Anda, 2010). These indicators were gathered under one latent factor. The residual error for the six indicators of primary caregiver emotional distress were allowed to covary to allow for methodological effects (T. A. Brown, 2015). Prior experimentation with this approach to ACEs modeling with the PSID-CDS has been shown to be acceptable (Olofson, 2017). This latent variable is presented in Figure 3.1a. The family conflict latent variable consisted of five variables. All indicators were conceptually aligned and used to construct one latent variable. This family conflict latent variable is presented in Figure 3.1b. The neighborhood quality latent variable is presented in Figure 3.1c. Consistent with theory, all variables were gathered into one latent variable of neighborhood quality, while residual covariance was specified for those indicators gathered under the same sub-constructs. That is, the “length of residency” and the “ability to identify strangers” indicators were specified with residual covariance because they are both related to the construct of neighborhood cohesion. Similarly, the two indicators of neighborhood safety were specified with residual covariance, and the four indicators of collective norms were specified with residual covariance. This approach allows for conceptually similar indicators to be gathered under a larger latent variable, rather than modeling multiple levels of latent variables. The cognitive outcomes variable consisted of the three tests of cognitive function contained in the PSID-CDS. The latent factor consisted of these three indicators with no residual covariance modeled, as shown in Figure 3.1d.

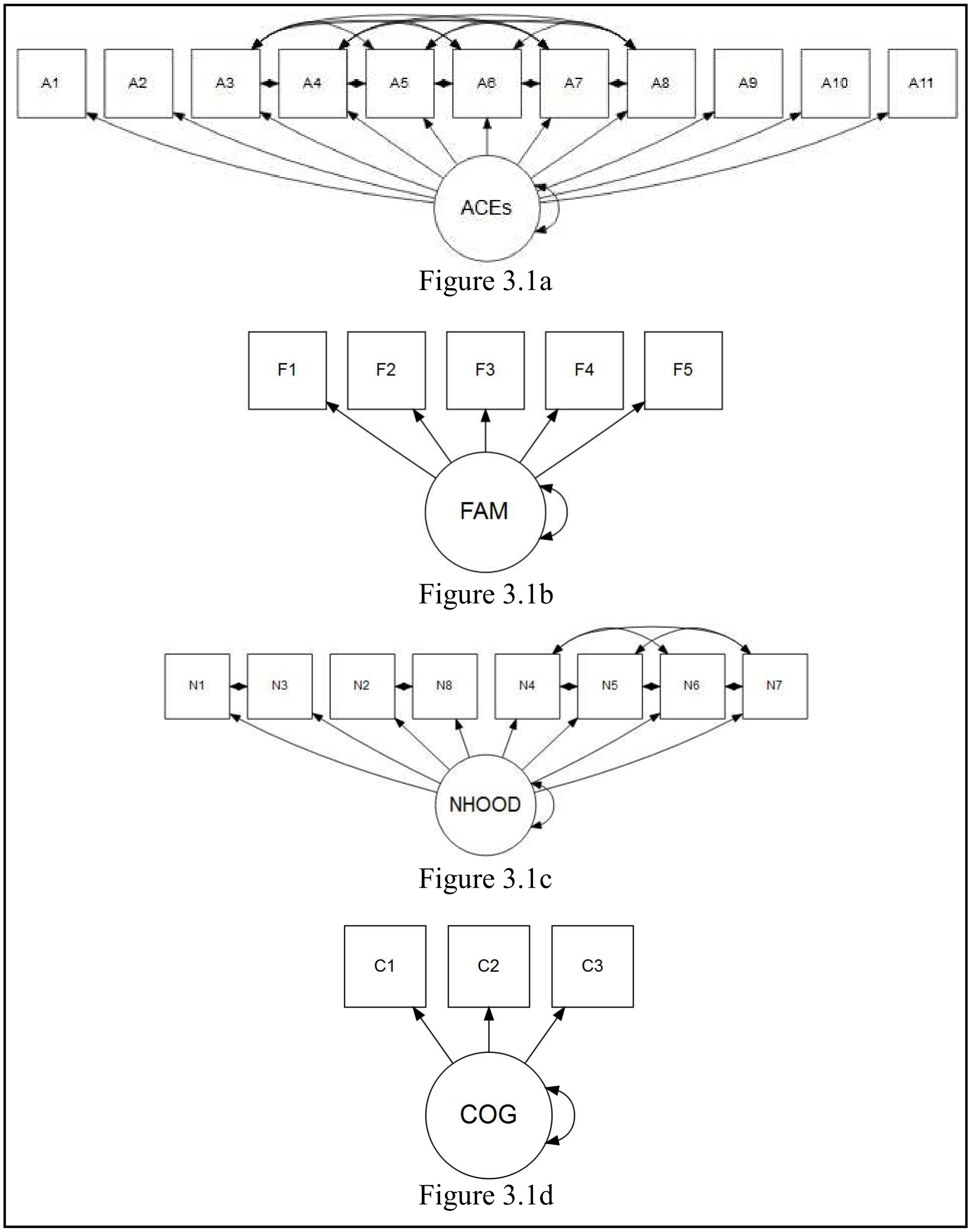

Figure 3.1: Latent models for ACEs, family conflict, neighborhood quality, and cognitive outcomes. The residuals associated with indicators A3 – A8 were allowed to covary (1a). The residuals for N1 and N3, N2 and N8, and N4 – N7 were allowed to covary (1c). For full variable descriptions see Table 3.2 and 3.4.

Following the theoretical construction, the psychometric properties of the ACEs, families, and neighborhood measures were assessed. The CFA procedure tested the factor structure of the latent variables for ACEs, family conflict, and neighborhood quality. The

CFA was performed with MPlus 7 (Muthén & Muthén, 1998) using the weighted least squares means and variances (WLSMV) method of estimation, due to the presence of categorical variables as indicators. The individual latent variables were evaluated for goodness of fit using the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the Tucker-Lewis index (TLI). For RMSEAs, values less than .08 and .05 were taken to reflect acceptable fit and excellent fit, respectively (T. A. Brown, 2015; Hu & Bentler, 1999). For CFI and TLI, values greater than .90 and .95 were taken to reflect acceptable fit and excellent fit, respectively (Bentler, 1990; T. A. Brown, 2015). The standardized root mean square residual (SRMR), a commonly used fit index in SEM, is not available with procedures using the WLSMV estimator, and consequentially was not used in these analyses.

The second stage of the analysis utilized structural equation modeling (SEM) to build increasingly complex and theoretically aligned relationships among these variables, consistent with bioecological development research functioning in the discovery mode (Bronfenbrenner & Morris, 2006). The first set of models in this stage tested the individual effects of ACEs, family conflict, and neighborhoods on the cognitive outcome variable. Shown in Figure 3.2, these models consisted of regressing the latent variable onto the exogenous variable, along with the control variables. In accordance with previous literature, it was hypothesized that all latent variables would individually have significant effects on the outcome, with increases in ACEs and family conflict being associated with decreases in cognitive function, and an increase in neighborhood quality being associated with an increase in cognitive function (Brooks-Gunn et al., 1993; Forehand et al., 1998; Jaffee & Maikovich-Fong, 2011).

The second set of models further operationalized the bioecological theory of development by measuring the effect of ACEs, families, and neighborhoods in conjunction with one another. These models are presented in Figure 3.3 and Figure 3.4. In the first approach, generalized in Figure 3.3, the outcome was regressed directly on all three latent indicators; the individual as modeled by ACEs and the two microsystems of families and neighborhoods. The covariance between the family and neighborhood latent variables was systematically freed and constrained to zero to test interactions between microsystems. The final group of models followed the bioecological approach of considering families and neighborhoods as separate microsystems, and modeled separate pathways from these microsystems through ACEs to the cognitive functioning outcome, as shown in Figure 3.4a. This model also tested for the direct effect of neighborhoods and family conflict on the outcome, as shown in Figure 3.4b. Models were evaluated for their comparative fit with the data, compared to each other using the WLSMV-adjusted Sattora-Bentler chi-square values (Satorra, 2000), and related to theory by the relative value and statistical significance of pathway coefficients.

Results

CFA

The results from the CFA with the individual latent variables indicated an overall an excellent model fit. The individual latent factor models are shown in Figure 3.1 along with the standardized factor loadings. These values were generated in a simultaneous CFA that allowed all individual latent variables to covary but introduced no other higher-order structure onto the latent variables. The RMSEA value for the model was .031, with a 90% confidence interval of 0.030 – 0.033. These values are well belo the commonly cited cutoff of .05 indicating excellent fit (Hu & Bentler, 1999). The CFI value was .955, above the cutoff of .950 indicating excellent fit, and the TLI value was .947, near the .95 cutoff for excellent fit and above the .90 cutoff indicating acceptable fit (Bentler, 1990; T. A. Brown, 2015). The factor loadings and commonalities for all indicators, along with their latent variables, are presented in Table 3.4. All standardized factor loadings were found to be statistically significant ($p < .05$), with nearly all loadings above the $\lambda = .30$ level commonly used to identify salient factors (T. A. Brown, 2015).

Table 3.4
Factor loadings, standard errors, and communalities from CFA results

Latent Variable	Indicator	Factor Loading	Standard Error	Communality	Standard Error
<u>*ACEs*</u>	A1: Biological parents	.332*	.039	.110*	.026
	A2: Alcohol use	.321*	.052	.103*	.033
	A3: Nervous	.274*	.031	.075*	.017
	A4: Hopeless	.438*	.036	.192*	.032
	A5: Restless	.260*	.031	.068*	.016
	A6: Effort	.335*	.034	.112*	.023
	A7: Sad	.452*	.037	.205*	.033
	A8: Worthless	.491*	.047	.242*	.046
	A9: Physical affection	.148*	.030	.022*	.009
	A10: Hostility	.679*	.025	.461*	.034
	A11: Warmth	.710*	.026	.505*	.036
	A12: Hit or threaten	.333*	.088	.111	.058
<u>*FAM*</u>	F1: Fight	.774*	.017	.599*	.026
	F2: Throw	.808*	.019	.653*	.030
	F3: Calm	.387*	.027	.150*	.021
	F4: Criticize	.634*	.021	.402*	.027
	F5: Hit	.655*	.023	.429*	.031
<u>*NHOOD*</u>	N1: Length of residence	.124*	.038	.015	.009
	N2: Place to raise kids	.817*	.044	.668*	.072
	N3: Strangers	.477*	.032	.228*	.031
	N4: Selling drugs	.663*	.046	.160*	.029
	N5: Kids in trouble	.400*	.037	.167*	.028
	N6: Disrespectful child	.408*	.034	.049*	.016
	N7: Child stealing	.222*	.035	.122*	.026
	N8: Safe after dark	.350*	.037	.440*	.061
<u>*COG*</u>	C1: Broad Reading	.813*	.022	.658*	.035
	C2: Applied Problems	.811*	.021	.661*	.037

C3: WISC	.452*	.026	.205*	.024

Note: * indicates $p < .05$

The covariance among these latent variables is presented in Table 3.5. These values were generated in the same analysis. With no other constraints applied, the latent variables were correlated at a moderate level, with higher values of ACEs, family conflict, and lack of neighborhood quality corresponding with lower values for cognitive outcomes. Given the acceptable to excellent fit of the latent variables, and the demonstrated relationships among the latent variables, all were utilized as modeled in further analyses. Additionally, all designated residual covariances demonstrated statistical significance ($p < .01$) and thus were similarly maintained in path analyses.

Table 3.5:
Latent variable correlations

	ACEs	*FAM*	*NHOOD*	*COG*
ACEs	1			
FAM	.482*	1		
NHOOD	.465*	.314*	1	
COG	-.427*	-.172*	-.305*	1

Note: * indicates $p < .05$

SEM

In the first SEM analyses, the ACEs, family, and neighborhood latent variables were modeled individually as predictors of cognitive outcomes. In these models, the cognitive outcome latent variable was regressed on the predictor variables one at a time. These models are shown in Figure 3.2. These individual models were also run with SES, gender, and race controls. Results from these analyses are presented in Table 3.6. These results indicate that, as hypothesized, as ACEs increase, cognitive outcomes decrease. Similarly, as family conflict increases, cognitive outcomes decrease. Additionally, as lack of neighborhood quality increases, cognitive outcomes decrease. All relationships between the individual latent variables and the outcomes were significant and robust to the introduction of demographic controls. Analysis of the control variables across the models show that children from higher SES backgrounds had higher assessment scores, and children of color had lower scores on these assessments than their white counterparts. In these models, gender did not have a statistically significant relationship with the cognitive outcome latent variable.

Table 3.6:
Cognitive outcomes on individual latent predictors (Figure 3.2)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ACEs	-.413*	-.195*				
FAM			-.169*	-.102*		
NHOOD					-.303*	-.090*
SES		.395*		.398*		.397*
Female		.020		.021		.021
Person of Color		-.188*		-.188*		-.188*
Communality						
R^2	.170*	.291*	.029*	.266*	.092*	.262*
Fit Statistics						
RMSEA	.035	.038	.043	.036	.040	.056
CFI	.974	.950	.973	.968	.987	.950
TLI	.963	.936	.960	.959	.979	.933

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

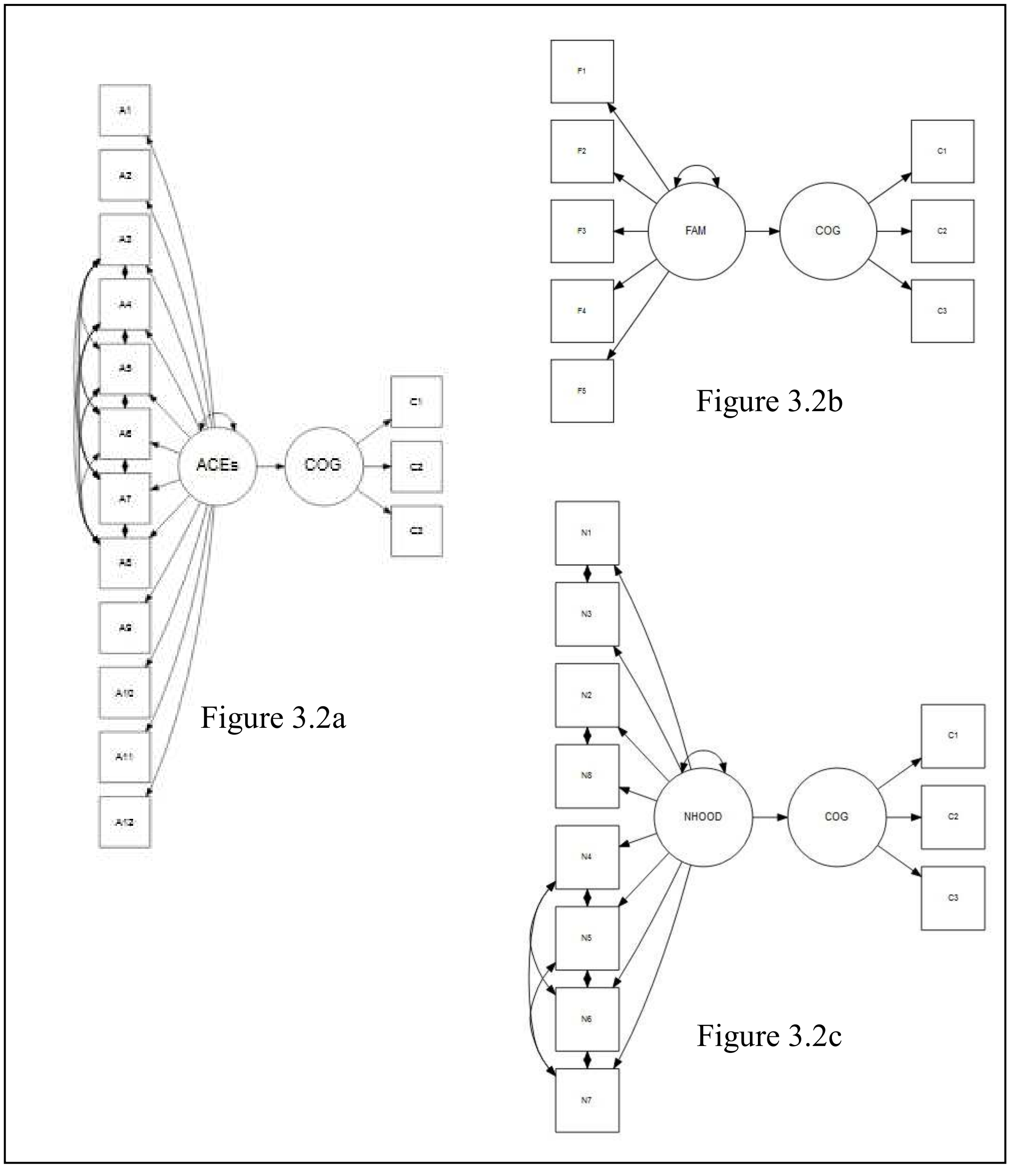

Figure 3.2: Individual models of ACEs, family conflict, and neighborhood quality as predictors for cognitive outcomes. See Table 3.6 for path coefficients. Not shown: control variables of socioeconomic status, gender, and race.

In the next group of SEM analyses, the cognitive outcome latent variable was regressed on the ACEs, family, and neighborhood latent variables simultaneously. The first set of models contained individual direct pathways from these latent variables to the outcomes. These models are visualized in Figure 3.3 and the results from these models are presented in Table 3.7. In the initial models, the latent variables were allowed to covary, and the model was tested with and without control variables (Table 3.7, Models 7 and 8). These results indicate that ACEs continue to have a significant negative relationship with cognitive outcomes when modeled in conjunction with family conflict and neighborhood quality. The addition of control variables to the model decreases the value of the path coefficient but does not eliminate statistical significance. The path coefficient from the family conflict latent variable to cognitive outcomes was not statistically significant, and while the path from the neighborhood latent variable to the outcome was statistically significant in Model 7, this relationship failed to maintain significant with the introduction of controls. The covariances among the latent variables were moderate and significant, functioned in the hypothesized direction, and were robust to the introduction of controls. Models 9 and 10 constrained the value of these covariances to zero. In these models, values for path coefficients for the family and neighborhood latent variables were larger and reached statistical significance, even when controls were introduced. The nested nature of Models 9 and 10 in Models 7 and 8 allowed for difference testing with the WLSMV-adjusted Satorra-Bentler chi-square values using the native procedure within MPlus (Muthén & Muthén, 1998). As expected, this test indicated that constraining the covariances among the latent variables significantly increased the misfit in the model, both across Models 7 and 9 ($\chi^2 = 324.372$; $df = 3$; $p < .01$) and Models 8 and 10 ($\chi^2 = 148.808$; $df = 3$; $p < .01$). This demonstrates the untenability of modeling ACEs, family conflict, and neighborhood quality as independently affecting cognitive outcomes.

Table 3.7:
Cognitive Outcomes on All Latent Predictors (Figure 3.3)

Variable	Model 7	Model 8	Model 9	Model 10
ACEs	-.389*	-.191*	-.415*	-.195*
FAM	.061	-.011	-.171*	-.103*
NHOOD	-.134*	-.038	-.304*	-.090*
SES		.395*		.395*
Female		.021		.021
Person of Color		-.189*		-.189*
Covariance				
ACEs with FAM	.484*	.423*	0	0
ACEs with NHOOD	.465*	.285*	0	0
FAM with NHOOD	.314*	.280*	0	0
Communality				
R^2	.199*	.297*	.294*	.309*
Fit Statistics				
RMSEA	.031	.036	.042	.039
CFI	.955	.922	.917	.907
TLI	.947	.910	.903	.894

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

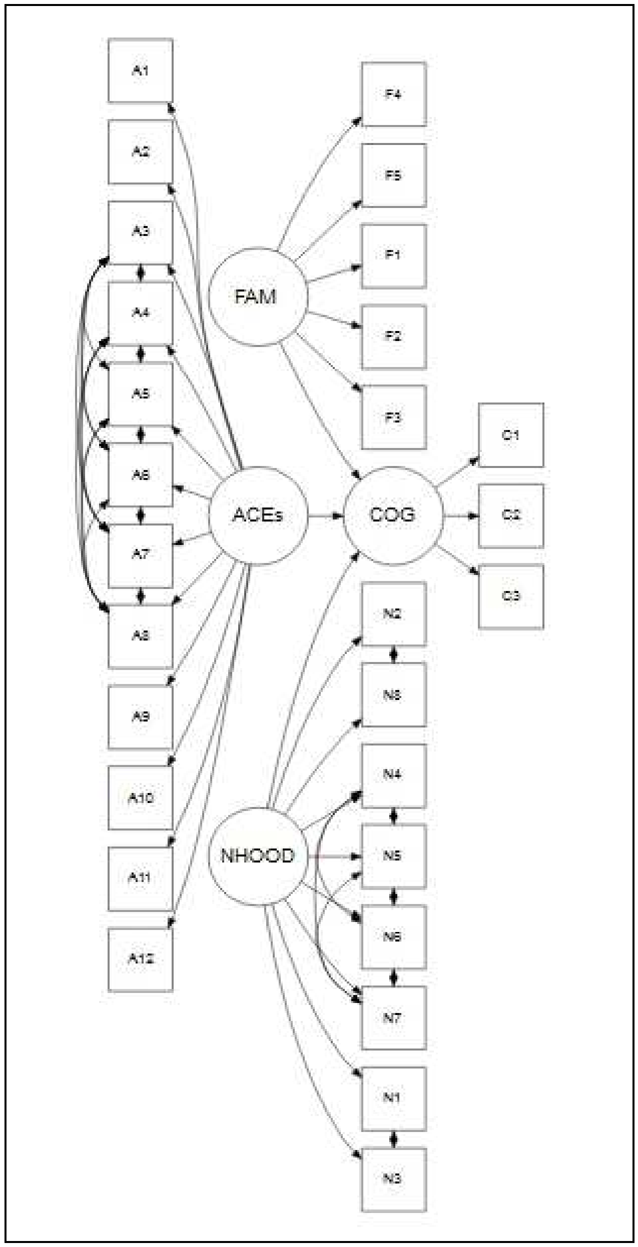

Figure 3.3: Path model of cognitive outcomes on ACEs, family conflict, and neighborhood quality. Predictor variables are modeled to function simultaneously on cognitive outcomes. See Table 3.7 for path coefficients. Not shown: control variables of socioeconomic status, gender, and race.

The final set of models provided two paths for development. As shown in Figure 3.4, one path modeled the proximal process between the neighborhood and the individual, while the other modeled the relationships between the family and the individual, with both paths leading through ACEs and to cognitive functioning. Similar to previous approaches, this model was tested with and without demographic controls. Path coefficients for these models (11 and 12) are presented in Table 3.8. All direct path coefficients reached statistical significance and function in the direction that would be expected given earlier results. The indirect path coefficients are included for these models, and demonstrate the statistical significance of the path of family conflict through ACEs to the outcomes and the path of neighborhood quality through ACEs to the outcomes. Models 13 and 14 introduce direct pathways along with the indirect pathways for family conflict and neighborhood quality to predict cognitive outcomes, testing with and without controls. Here, the family conflict latent variable no longer reached statistical significance as a predictor for cognitive outcomes, nor did neighborhood quality, once controls were introduced (Model 14). While the indirect effect of family conflict is negative and significant, the direct path coefficient is small, positive, and not statistically significant. The results for the neighborhood quality variable are qualitatively the same. Using difference testing, the removal of the direct pathways from neighborhood quality to outcomes and family conflict to outcomes only marginally increased the misfit for the data for the model without controls, and did not significantly increase the misfit for the models with controls when compared to the models with the direct pathways for ACEs (Model 13 and 11: $\chi^2 = 10.270$; $df = 2$; $p < .01$; Model 14 and 12: ($\chi^2 = 1.136$; $df = 2$; $p > .01$). These results offer empirical support for omitting a direct pathway from the family conflict and neighborhood quality variables to the cognitive outcomes.

Table 3.8:

Cognitive outcomes on ACEs, ACEs on family conflict and neighborhood quality (Figure 3.4)

Variable	Model 11	Model 12	Model 13	Model 14
COG on ACES	-.455*	-.220*	-.389*	-.191*
ACES on FAM	.345*	.373*	.372*	.372*
ACES on NHOOD	.397*	.192*	.348*	.181*
COG on FAM (Indirect)	-.157*	-.082*	-.145*	-.071*
COG on NHOOD (Indirect)	-.180*	-.042*	-.136*	-.035*
COG on FAM (Direct)			.061	-.011
COG on NHOOD (Direct)			-.143*	-.038
SES		.395*		.395*
Female		.021		.021
Person of Color		-.189*		-.188*
Covariance				
FAM with NHOOD	.315*	.280*	.315*	.280*
Communality				
R^2 (COG)	.207*	.310*	.199*	.297*
R^2 (ACES)	.363*	.216*	.341*	.209*
Fit Statistics				
RMSEA	.031	.036	.031	.036
CFI	.955	.924	.955	.922
TLI	.947	.913	.947	.910

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

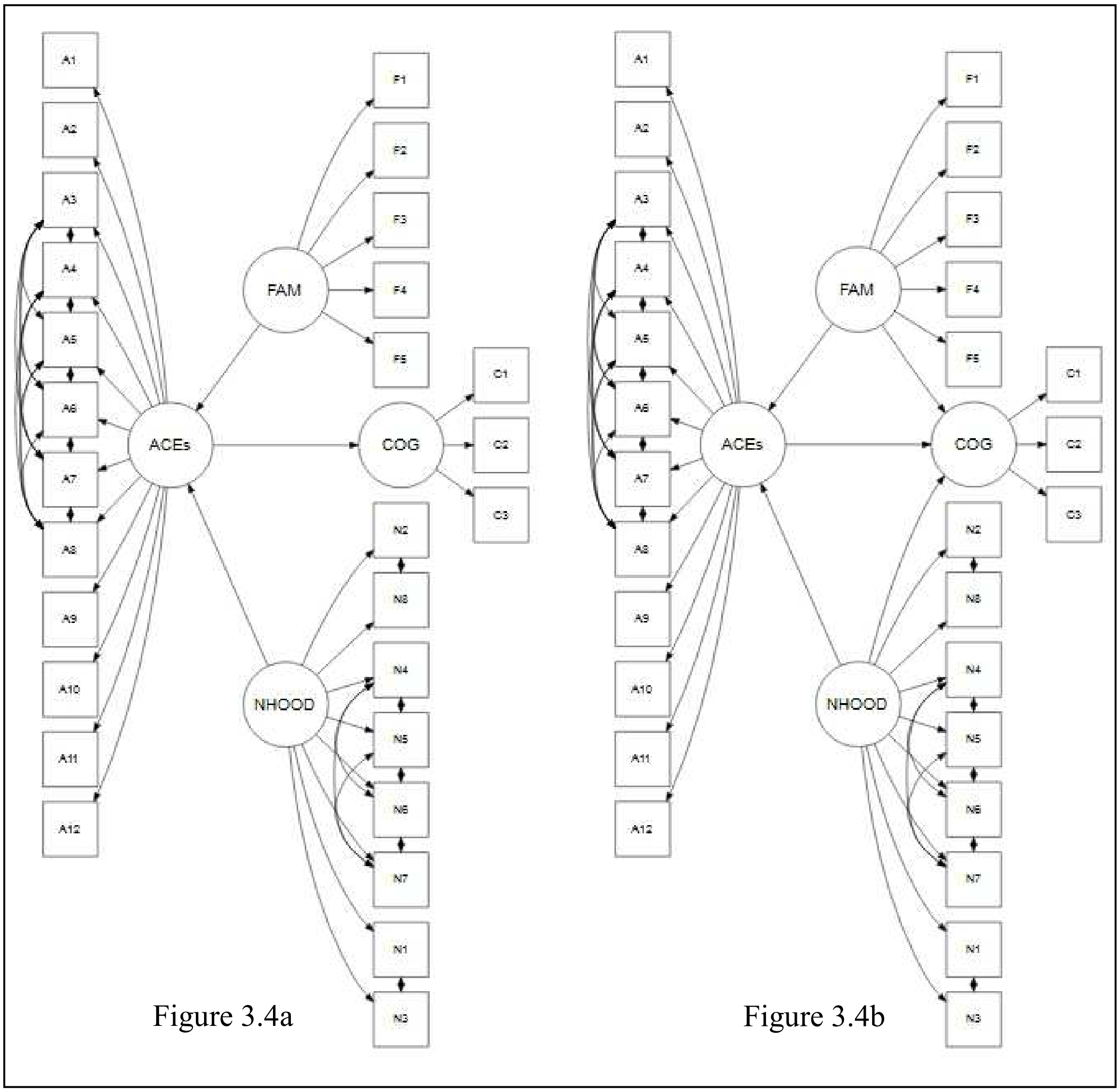

Figure 3.4: Path models aligned with interpretation of the bioecological model of development. Family conflict and neighborhood quality modeled as microsystems influencing individual as modeled by ACEs. See Table 3.8 for path coefficients. Not shown: control variables of socioeconomic status, gender, and race.

Discussion

The purpose of this study was to investigate the relationships among ACEs, family conflict, neighborhood quality, and cognitive outcomes using the bioecological model of development as a guiding theoretical framework. Results from the initial CFA indicated that the latent variables of ACEs, family conflict, and neighborhood quality all represented acceptable to excellent fit for the data in the PSID-CDS. These findings are in alignment with previous studies of ACEs that use a latent factor approach with the PSID-CDS and other data sets (e.g., M. J. Brown, Perera, Masho, Mezuk, & Cohen, 2015; Ford et al., 2014; Olofson, 2017). The fit of the family conflict variable containing indicators ranging from physical and relational dysfunction supports the utility of such dimensions as used elsewhere (e.g., S. E. Evans et al., 2008; Forehand et al., 1998). Additionally, the results from the neighborhood latent model support the modeling of neighborhoods using dimensions of cohesion, collective norms, and safety (Burdick-Will et al., 2011; Galster, 2012; Sampson, Morenoff, & Gannon-Rowley, 2002). With respect to the bioecological model of development, the results from the CFA provide evidence for these dimensions of individuals, along with the microsystems of families and neighborhoods, to be measured in such as way. This provided a foundation for the rest of the analyses.

Results from the first group of SEM analyses indicate significant regression coefficients when ACEs, family conflict, and neighborhood quality are individually regressed on cognitive outcomes. These findings align with existing research about ACEs (Bethell et al., 2014; Jaffee & Maikovich-Fong, 2011), families (S. E. Evans et al., 2008; Sheeber et al., 1997), and neighborhoods (Burdick-Will et al., 2011; G. J. Duncan & Magnuson, 2011). The results from the models with demographic control variables indicate the presence of race and SES gaps in achievement, also consistent with research (Sirin, 2005; Todd & Wolpin, 2007). The models do not show a gap in achievement related to gender when achievement across subject areas is combined (Hyde, Lindberg, Linn, Ellis, & Williams, 2008; Perie, Moran, & Lutkus, 2005). These models provide empirical support for the inclusion of adversity at the individual level along with along with the microsystems of families and neighborhoods in the theoretical model.

The results from Models 7-10, which incorporated all three predictors, indicate that the effect of ACEs, family conflict, and neighborhoods cannot be disentangled from one another. The covariances among these variables are statistically significant, and remained so when demographic controls were introduced into the structural model. Additionally, when the covariances were constrained to zero, the fit of the models significantly decreased. This supports the notion from bioecological theory that the individual is nested within microsystems, and that the microsystems cannot be considered as independent from each other. The path coefficients for the family conflict and neighborhood quality variables decrease in value and fail to reach statistical significance when covariances across the latent variables are freely estimated. The covariances between ACEs and the microsystem variables of families and neighborhoods are moderate in size, statistically significant, and robust to the introduction of controls. This points to proximal processes occurring at the junction of the individual and these contexts with implications for cognitive functioning. The microsystems do not independently relate to cognitive outcomes, rather, they act in conjunction with ACEs. The covariance between families and neighborhoods demonstrates the relationship between microsystems. This covariance is significant and robust to the introduction of controls. While family conflict and neighborhood quality have been shown repeatedly to be related to cognitive outcomes (Burdick-Will et al., 2011; G. J. Duncan & Magnuson, 2011; S. E. Evans et al., 2008), this indicates difficulties in conceptualizing these microsystems as independent from adversity at the individual level.

Following this conclusion, the two-path models treated family conflict and neighborhood quality as microsystems functioning through the individual as measured by ACEs. These models clarify the relationships between the family and neighborhood microsystems with cognitive outcomes. When the models with direct pathways from family conflict and neighborhood quality to outcomes are compared to those without, the function of these latent variables is revealed to be through the individual, as measured by the indirect effect, rather than an independent function, as measured by the direct effect. This also highlights the central role of ACEs in predicting cognitive outcomes. This model demonstrates the continued relationship between individual adversity and the microsystems of families and neighborhoods; however, these findings indicate a lack of evidence for a separate effect of these pathways on cognitive outcomes. Family conflict and neighborhood quality matter, but they cannot be used as predictors of cognitive outcomes without the inclusion of individual adversity.

The question of causality limits the interpretations offered by the results in this study. Given the lack of randomization, treatment, or isolation of causal influencers in the experimental design, utilization of statistical methods to test causality are not available (Kline, 2015; Mulaik, 2009). However, according to Bronfenbrenner (1976), research in bioecological development must necessarily happen within the natural context, removing such research designs from the realm of possibility within this theoretical context. Causality is further threatened due to the use of cross-sectional data. When using concurrent measurement in SEM, "the sole basis for causal inference in such designs is assumption, one supported by a convincing, substantive rationale…" (Kline, 2015, p. 125). This study assumes that individual adversity, family conflict, and neighborhood quality are less influenced by the cognitive functioning of the individual than they are influencers of that cognitive function. Neighborhoods and, to a lesser extent, families contain more people and have longer history than any one individual, meaning that the cognitive functioning of that individual has a negligible effect. Likewise, the indicators for ACEs are dependent on the attitudes and actions of caregivers, who likely have numerous stimuli other than the individual shaping those attitudes and actions. For these reasons this study treats cognitive function as an outcome rather than a predictor with respect to ACEs, families, and neighborhoods. However, additional research to investigate the direction of the causal arrow would help to clarify these issues.

Future research using the final model which highlighted the presence of an indirect effect but the lack of a direct effect from family conflict or neighborhood quality to cognitive outcomes could be conducted to observe shifts in this phenomena across developmental groups. Individuals interact with developmental contexts differently at different ages, changing the ways in which contexts drive development, along with the extent to which they have an effect (Sameroff, 2010). This study utilized a wide sample of children from different developmental stages. Analysis of subsamples consisting of individuals in developmental groups could further elaborate on the relationships between the individual and the family and neighborhood contexts and how they are different at different stages. This study can serve as a reference point for such a line of research.

Conclusion

The bioecological model of human development posits that contexts and individuals interact directly and indirectly to drive development. Consequentially, knowledge of contexts and the individual should be able to partially predict developmental outcomes. This study explored the relationships between ACEs, family conflict, neighborhood quality, and cognitive functioning. The first guiding question, which asked if the measures of the individual, families, and neighborhoods produced the type of relationships with cognitive outcomes that would be predicted by existing research, can be answered in the affirmative. All three of the predictor variables demonstrated a good fit for the data, the paths from adversity and family conflict to cognitive outcomes were negative and significant, and the path from lack of neighborhood quality to cognitive outcomes was negative and significant. The second guiding question inquired as to nature of the path from family conflict to cognitive outcomes and the path from neighborhood quality to cognitive outcomes. It was found that individual childhood adversity cannot be disregarded in this modeling, and that whereas a direct pathway from ACEs to cognitive outcomes is empirically supported, direct pathways from the proximal contexts are not. This finding highlights the importance of measurement at the individual level, along with the incorporation of measures of developmental contexts, for understanding development that affects cognitive outcomes and long-term achievement.

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CHAPTER 4

The Role of School Safety Factors in Supporting Pre- and Young Adolescents with Adverse Backgrounds

Introduction

Beginning in early childhood, children interact with schools in ways that greatly influence their ongoing development (Eccles & Roeser, 2011). Schools have an effect on development as children interact directly with the individuals, groups, and structures of the school (Berns, 2010; Bronfenbrenner, 1976). Schools act as tools of society to support children's development using educational, organizational, and social elements (Berns, 2010). The impact of schools can be shaped by the school climate, a main component of which is school safety (Berns, 2010; Thapa, Cohen, Guffey, & Higgins-D'Alessandro, 2013). School security is an important component of schools, impacting cognitive outcomes in children (Cook, Gottfredson, & Na, 2010). However, schools are but one of a constellation of systems that influence development.

The bioecological model of human development offers several contextual factors that influence development along with schools (Bronfenbrenner & Morris, 2006). Other proximal contextual factors, including families and neighborhoods, are impactful (Bronfenbrenner, 1986; Jensen & Chen, 2013). Models can be constructed that relate measures of these contextual factors to outcomes of interest. However, as pointed out by Darling (2007), the individual should not be overlooked in these contextual models. One widely used measurement of the individual that can be used in conjunction with these measures of school, family, and neighborhood contexts is the Adverse Childhood Experiences (ACEs) framework. ACEs have been incorporated in models that include other proximal factors to demonstrate their deleterious effects on academic and cognitive outcomes (Bethell, Newacheck, Hawes, & Halfon, 2014; Jaffee & Maikovich-Fong, 2011). Such negative impacts are apparent even in the pre-adolescent years (Hindman, Skibbe, Miller, & Zimmerman, 2010).

Positive changes to school climate, including school safety, can have positive impacts on school outcomes, along with later in life economic outcomes (Center for Promise, 2015). Children with varying levels of ACEs are affected by changes in school climate (Cassen, Feinstein, & Graham, 2009). Crucially, targeted interventions that help support children from adversity can serve to close gaps and support the long-term well-being of these children (G. J. Duncan & Murnane, 2014). However, such changes may serve as a resource, supporting positive changes for all students, or be a protective factor, providing differential supportive effects for children from different levels of adversity (Conrad & Hammen, 1993; Hammen, 2003). If changes to school safety can differentially support students from higher levels of adversity, then such reforms can serve to lessen the gaps between students from low adversity and high adversity. However, in order to demonstrate the presence of such a protective factor and to advocate for such reforms as addressing this gap, the relationships between adversity, schools, and cognitive outcomes must be modeled in such a way as to incorporate influential contextual factors. The purpose of this study is to construct such a model guided by to the bioecological framework of human development in order to investigate the nature of the relationship between school safety and cognitive outcomes in young people with varying levels of adversity.

Background

A better understanding of developmental aspects of pre- and young adolescents is a central question for educational researchers (Middle Level Education Research Special Interest Group, 2016; Rimm-Kaufman & Pianta, 2000). While there are numerous approaches to describing and modeling development (Sameroff, 2010), this study utilizes a bioecological approach that incorporates measures of the individual and the developmental contexts (Bronfenbrenner, 1976; Bronfenbrenner & Evans, 2000; Darling, 2007). This contextual approach incorporates the multiple influences on pre- and young adolescents that occur outside the school building that can affect their cognitive and academic achievement (Rimm-Kaufman & Pianta, 2000). This allows for a more refined observation of the influence of school safety on pre- and young adolescent achievement than would be provided by relating outcomes to school safety alone.

Developmental influences

Human development occurs through the interplay between the individual and the elements in their proximal and distal contexts (Bronfenbrenner, 1976, 1996; Bronfenbrenner & Morris, 2006). While Piaget (1954) outlined the individual's processes of assimilation and accommodation describing the individual and the direct interface with the outside world, the bioecological model of development posits that both individuals and the people, objects, and symbols in their environment grow or change through these interactions, contributing to competence or dysfunction (Bronfenbrenner & Morris, 1998). Additionally, the contexts themselves interact, and such distal processes are recognized as influencing the individual (Bronfenbrenner & Evans, 2000). This bioecological perspective is used by the World Health organization (Blas & Kurup, 2010) and the US Department of Health and Human Services (2010), among other influential organizations to conceptualize various phenomena and conduct research related to human development and public health.

Scholars utilizing the bioecological model argue that understandings of the contexts and the processes through which they interrelate are necessary to describe development (Bronfenbrenner & Morris, 2006). These contexts include layers or levels of interconnected systems; microsystems are the contextual elements with which the individual directly interacts (Bronfenbrenner, 1994). As described by Sameroff (2010), as individuals pass through developmental stages, the nature of their relationships with different contexts change. In early childhood and young adolescence, families, neighborhoods, and schools are influential microsystems (Berns, 2010; Bronfenbrenner, 1986; Eccles & Roeser, 2011; Jensen & Chen, 2013; Rimm-Kaufman & Pianta, 2000). Such systems can be modeled using dimensions that have been shown to be related to outcomes of interest. Additionally, in such bioecological models, the individual and his or her characteristics must also be included (Darling, 2007). A bioecological or contextual perspective of development is but one interrelated way to view development, and utilizing this framework examines only a part of a larger dynamic system of development (Sameroff, 2010). However, the integration of the individual and the microsystems of families, neighborhoods, and schools in modeling cognitive functioning introduces a more situated view of development than models that depend upon any one of these developmental contexts alone (Eccles & Roeser, 2010; Rimm-Kaufman & Pianta, 2000).

ACEs. Adversity in childhood is a key contributor to predicting later-in-life outcomes and can be used in conjunction within a model of development that considers contextual elements (Center for Disease Control and Prevention, 2015). The Adverse Childhood Experiences (ACEs) framework is a framework for childhood adversity that is widely used in public health and the social sciences (Center for Disease Control and Prevention, 2015; Felitti et al., 1998; Larkin, Felitti, & Anda, 2014; McLaughlin, Sheridan, & Lambert, 2014). The framework was originally constructed by Felitti and colleagues (1998), and consists of measures of abuse, neglect, and household dysfunction (Felitti et al., 1998; Felitti & Anda, 2010). ACEs have been linked with deleterious repercussions in adulthood, including physical and mental health outcomes (Center for Disease Control and Prevention, 2015; Felitti et al., 1998). The negative impact of ACEs has been shown to be measurable during childhood and adolescence. Similar to studies of adults, children and young adolescents who experience ACEs also tend to report a higher rate of anger, depression, anxiety, and dissociation (Finkelhor, Shattuck, Turner, & Hamby, 2013; Marie-Mitchell & O'Connor, 2013). Higher rates of ACEs have also been shown to be predictive of lower rates of engagement at school (Bethell et al., 2014). The negative impacts of ACEs, along with their connections to other contextual elements, are apparent early in a child's life (Hindman et al., 2010).

Family Conflict. In the bioecological framework, families can be modeled as microsystems that influence development (Berns, 2010; Bronfenbrenner, 1986). The conflict within the family negatively impacts the development and potential for adaptation within a young person (Cicchetti, 2013). The negative impact of exposure to family conflict on behavioral outcomes is apparent in early adolescence (Evans, Davies,

& DiLillo, 2008). Children exposed to familial conflict experience negative impacts on educational outcomes in both the short and long term (Forehand, Biggar, & Kotchick, 1998). Alternately, high quality family relationships can prevent and support positive school engagement for elementary and middle school students (Henry & The Multisite Violence Prevention Project, 2012). Conflict within the family has been modeled using indicators of physical and relational hostility (Evans et al., 2008; Herrenkohl, Kosterman, Hawkins, & Mason, 2009; Lyerly & Brunner Huber, 2013). No matter their function, families do not exist in isolation, and the interplay between families and other developmental contexts is complex and mixed (Briggs, Popkin, & Goering, 2010).

Neighborhood Quality. Neighborhoods are a proximal context with which young people interact directly and indirectly, contributing to their overall development (Berns, 2010; Bronfenbrenner & Morris, 2006; Sharkey & Elwert, 2011). The quality of these neighborhoods can have both positive and negative influences on developmental outcomes (Leventhal & Brooks-Gunn, 2000; Sharkey & Faber, 2014). Neighborhood quality can be measured using dimensions of neighborhood cohesion, collective norms, and safety (Galster, 2012; Jencks & Mayer, 1990; Leventhal & Brooks-Gunn, 2000). Cohesion and collective social norms are part the larger social interaction mechanism that governs neighborhoods (Galster, 2012). Neighborhood violence or safety is generally conceptualized as a separate but vital element of neighborhoods that has an impact on children (Fowler, Tompsett, Braciszewski, Jacques-Tiura, & Baltes, 2009; Galster, 2012). Both social interaction mechanisms such as cohesion and collective norms and environmental mechanisms such as safety have been shown to have development impacts (Brooks-Gunn, Duncan, Klebanov, & Sealand, 1993; Burdick-Will et al., 2011; Fowler et al., 2009). Relationships between adversity, families, and neighborhoods, and cognitive outcomes can be observed in pre- and young adolescence (Cleveland, 2003; G. J. Duncan, Boisjoly, & Harris, 2001; G. J. Duncan & Murnane, 2011; Rimm-Kaufman & Pianta, 2000). However, the microsystem of schools cannot be excluded when modeling this development (Bronfenbrenner & Morris, 1998; Eccles & Roeser, 2011)

School Safety and Development

"From the time individuals first enter school until they complete their formal schooling, children and adolescents spend more time in schools than in any other place outside their homes" (Eccles & Roeser, 2010, p. 6). In the ecological model of human development, school can be conceptualized as a microsystem that influences development through direct interaction with the individual (Berns, 2010; Bronfenbrenner, 1976). Schools provide supports that promote cognitive and behavioral development for elementary and middle school students (Eccles & Roeser, 2011). Schools have goals that extend to the academic, vocational, social, and personal, including cognitive and emotional development (Berns, 2010). Along with other microsystems, schools can affect academic and socioemotional outcomes for children from adversity by fostering resilience (Cassen et al., 2009).

School climate, broadly conceived, is "the quality and character of school life" (National School Climate Council, 2007, p. 5). School climate affects the academic, social, and emotional achievement of students (National School Climate Council, 2007; Thapa et al., 2013; U.S. Department of Education, 2012). Positive school climate "fosters youth development and learning necessary for a productive, contributing and satisfying life in a democratic society" (National School Climate Council, 2007, p. 5). Cohen and

Geier (2010) identified four dimensions of school climate: safety, relationships, teaching and learning, and the institutional environment. The U.S. Department of Education recognize three dimensions of engagement, safety, and environment (2012). While frameworks for defining school climate abound, an element of safety is consistently included (National School Climate Council, 2007; Thapa et al., 2013; U.S. Department of Education, 2012).

School safety, including rules, norms, physical safety, and social-emotional safety, is a dimension of the school that has a developmental impact (Thapa et al., 2013). As summarized by Steffegen, Recchia, and Veichtbauer (2013), school violence can be conceptualized as student engagement in aggressive behaviors, including physical aggression, verbal aggression, and weapon use. Theft, vandalism, and drug use can be conceptually linked with violence for a larger portrait of the criminal environment in schools (Cook et al., 2010). The U.S. Department of Education (2012) identifies five dimensions of school safety, including emotional safety, physical safety, bullying/cyberbullying, substance abuse, and emergency readiness and management. This physical safety dimension refers to the safety of everyone involved in schooling, including the students, faculty, and staff, as the safety of all stakeholders impacts the overall school climate.

Safe schools are particularly important for elementary and middle school students who are engaging in building the foundation of their relationship to school (National School Climate Council, 2007; U.S. Department of Education, 2012; Voight & Hanson, 2017). A high quality school climate where students and teachers alike are safe is positively associated with better academic and developmental outcomes (Cohen & Geier, 2010; Osher, Spier, Kendziora, & Cai, 2009; U.S. Department of Education, 2012). Alternately, negative school environments that include drug and alcohol use or violence in the halls have been shown to negatively impact academic outcomes for students (Cook et al., 2010). Positive changes to school climate, including school safety, can have positive impacts on school outcomes, along with later in life economic outcomes (Center for Promise, 2015; Osher et al., 2009; Voight & Hanson, 2017). However, the relationship between school safety and academic outcomes is neither simple nor direct (Altonji & Mansfield, 2011; Herrenkohl et al., 2009).

Although researchers have found differences in the impact of school safety and violence based on demographic variations, these findings have not been homogenous. In their small-scale study of perceptions of the school environment and school security, Mester and colleagues (2015) found evidence that feelings of security differ by whether a student is African American or Caucasian. Different elements of the school environment with respect to school security affect student perceptions differentially by race (Bachman, Randolph, & Brown, 2011). Alternately, Tanner-Smith and Fisher (2016) found no evidence of race acting as a moderator in students' perceptions of safety. Hong and Eamon (2012) found differences in the perception of school security and environment across different genders and ages of students. However, in their meta-analysis of the effects of school violence on perception of the school climate, Steffecan and colleagues (2013) found no moderating effects of gender or age. There also appears to be a difference among students from different socioeconomic levels (Bachman et al., 2011; Tanner-Smith & Fisher, 2016).

The differences in outcomes for different demographic groups indicate that schools do not have an independent, decontextualized effect on students. In their study using three longitudinal data sets, Altonji and Mansfield (2011) found only modest effects of schools on the eventual economic outcomes for students, when controlling for family-level factors. For students with adverse backgrounds, a personal connection to their high schools did not provide significant mediating effect on the relationship between their background and eventual adult socioemotional outcomes (Herrenkohl et al., 2009). The Center for Promise (2015) found that above a certain rate of adversity, social supports are not enough to prevent dropping out of high school. The school environment interacts with the characteristics of the child as well as other microsystems in the way that it influences academic and socioemotional outcomes (Cassen et al., 2009). Student perceptions of the school climate have been demonstrated to be correlated to the occurrence of negative behaviors in young adolescences (Loukas & Robinson, 2004; Wang, Selman, Dishion, & Stormshak, 2010).

Purpose of this Study

Although safe and supportive school environments are necessary for pre- and young adolescents to be successful, these environments cannot be isolated from other developmental influences such as family conflict or neighborhood quality (Berns, 2010; Bronfenbrenner, 1976; Bronfenbrenner & Morris, 2006). Studies of the relationship between school environments and cognitive function have produced mixed results (Hong & Eamon, 2012; McEwin & Greene, 2010; Tanner-Smith & Fisher, 2016). However, such studies have not focused on pre- and young adolescents while employing multiple developmental influences to focus on school environments (Ciula & Skinner, 2015; R.

Thompson et al., 2015). Additionally, since targeted interventions that help support children from adversity can serve to close achievement gaps (G. J. Duncan & Murnane, 2014), this study measures if there are differences when comparing the relationships between school environments and cognitive outcomes across adversity levels. The purpose of this study is to observe and measure the path from school climate operationalized using the dimension of school safety to cognitive outcomes for pre- and young adolescents using a nationally representative data set. This study was guided by two related questions:

1. Are increases in the school safety conditions related to cognitive functioning of students in kindergarten to seventh grade when schools are modeled as a microsystem functioning through the individual?
2. Is the relationship between school safety and cognitive outcomes different for students from high adversity backgrounds when compared to students from lower adversity backgrounds?

Results from this study could be used to help shape policy regarding the environments of schools, and the practices in place in elementary and middle schools particularly, to better meet the needs of students from adversity.

Data and Methods

This section presents a description of the Panel Study of Income Dynamics Child Development Supplement (PSID-CDS), along with the variables and sample taken from the PSID-CDS used in this study. This is followed by a description of the analyses, which employed structural equation modeling (SEM) as the central approach to providing answers to the research questions.

Instrument

The data used in this study comes from the PSID-CDS, which is a subset of the Panel Study of Income Dynamics (PSID), an ongoing study of the economic and life course development of families in the United States (McGonagle, Schoeni, Sastry, & Freedman, 2012). The PSID was launched in 1968 with a nationally representative sample of families, and has subsequently followed those families and their progeny by collecting data annually or semi-annually on hundreds of economic and quality of life variables. In 1997 the PSID launched the PSID-CDS to better understand the lives of children. The PSID-CDS collected data on over 500 variables about the lives of the children in PSID families (Hofferth, Davis-Kean, Davis, & Finkelstein, 1997). Information about children was collected from caregivers, educators, and the children themselves. The PSID-CDS provides useful data for researchers investigating childhood adversity (e.g., Björkenstam et al., 2015; Ciula & Skinner, 2015). Additional waves of PSID-CDS data were collected in 2002 and 2007. The research questions in this study focus on schools; therefore, the data from the 2002 wave (PSID-CDS II) was used in this study because it provided the maximum school-aged sample of the three waves.

Sample

The PSID-CDS II sample consists of 2907 children ages 5-17, drawn from families in the PSID core sample (Institute for Social Research, 2010). At the initiation for the PSID-CDS in 1997, all PSID families living in the continental U.S. with a child under the age of 13 were included in the sample. In families with one or two children under 13, all children were included in the sample. In families with more than 2 children in the age range, two children were randomly selected by the PSID to be in the sample (Hofferth et al., 1997).

Of particular interest to this study is the data collected from the teachers of the sampled children. Parents of school-aged children in the 2002 PSID-CDS sample were asked if contact could be made with the teacher; 76% of parents consented (Institute for Social Research, 2010). Although response rate in the overall PSID-CDS sample was high, the response rate from middle and elementary school teachers was comparably low, as just 699 teachers responded out of the eligible pool of 1305 (Institute for Social Research, 2010). Students with partially or fully completed school surveys constituted the sample used in this study. Following the PSID-CDS technical documents, the primary caregiver/child weight was used in this analysis, which balances the sample on race, geographic location, urbanicity, and level of education of the head of household (Gouskova, 2001). When applied, this weight, based on the original sample (N=2907), inflates the sample size. The weight was normalized by dividing the values by the total weighted sample size and multiplying by the original sample size, which aids in interpretation. Following the application of weights, the working sample was reduced to 683 students from grades K-7. A summary of the demographic characteristics of the PSID-CDS Education 2002 sample used in this study is presented in Table 4.1.

Table 4.1
Demographic characteristics of PSID-CDS Education 2002 sample

Category	Classification	Percent of Sample
Gender	Male	54.0
	Female	46.0
Race	Person of Color	70.0
	White	27.2
Census Region	Northeast	16.9
	North Central	22.0

	South	32.5
	West	28.3
Urbanicity	Metropolitan Statistical Area	64.0
	Non-Metropolitan Statistical Area	35.7
Head Education Level	Did not graduate high school	17.7
	Graduated high school	74.8
School Grade Level	Kindergarten	9.1
	First Grade	18.3
	Second Grade	20.0
	Third Grade	14.4
	Fourth Grade	20.1
	Fifth Grade	14.6
	Sixth Grade	3.3
	Seventh Grade	0.1

Note: Percentages based on weighted data. Sum of group percentages < 100% due to missing data.

Variables

This study uses indicators taken from the PSID-CDS II to measure the latent predictor variables of ACEs, family conflict, neighborhood quality, and school safety. These variables are presented Table 4.2, grouped by their associated latent variable. The set of ACEs indicators consisted of 11 variables aligned with the original ACEs framework (Felitti et al., 1998; Felitti & Anda, 2010). This measure has previously demonstrated an excellent fit for this data and has been used in applied work (Olofson, 2017a, 2017b). For analytical clarity, a simplified one-factor model of ACEs was used in this study with only those variables that demonstrated variability on all measures in the PSID-CDS Education 2002 sample. The family latent variable was measured using the variables from a five-item scale of familial conflict resolution that originated in the National Survey of Families and Households (Institute for Social Research, 2010). The neighborhood quality measure consisted of eight items that were originally crafted for the National Longitudinal Study of Youth, the Denver Youth Study, and the Project on Human Development in Chicago Neighborhoods (Institute for Social Research, 2010).

The eight indicators of school safety were part of a set of questions new to the PSID-CDS given to elementary and middle school teachers to obtain information about the school environment (Hofferth et al., 1997). These questions prompted teachers to report if different threats to school safety were “not a problem”, “somewhat of a problem”, or “a serious problem” in their schools. Responses were collapsed into a binary by gathering the “somewhat” and “serious” responses, as they indicated that the threat was present in the school. This reduction in categories was necessary so that all school safety could be interpreted in the same way, as some indicators did not have responses in all three categories. A review of the literature citing the PSID-CDS hosted by the PSID yields no instances of these questions being used previously in analyses. Although collected from teachers, as noted by Montoya and Brown (1989), teachers of young adolescents are likely to provide similar ratings of school climate as their students. All together, 32 variables were used to construct the latent variables describing the individual and his or her developmental contexts. Except where noted in Table 4.2, variables were used without transformation. Due to the limited range of response options, all variables were treated as categorical in modeling except where otherwise noted.

Table 4.2
ACEs measures from the PSID-CDS

Latent Variable	Variable	N*	Scale
Adverse Childhood Experiences (ACEs)	Both biological parents present[a]	669	Dichotomous
	Disagreement about alcohol use	671	Dichotomous
	Primary Caregiver: nervous	673	5-point Likert Scale: Frequency
	Primary Caregiver: hopeless	671	5-point Likert Scale: Frequency
	Primary Caregiver: restless	671	5-point Likert Scale: Frequency
	Primary Caregiver: everything an effort	668	5-point Likert Scale: Frequency

	Primary Caregiver: sad	671	5-point Likert Scale: Frequency
	Primary Caregiver: worthless	671	5-point Likert Scale: Frequency
	Physical affection[b]	622	Continuous
	Hostility towards child[c]	614	5-point Likert: Intensity
	Warmth towards child[b,c]	614	5-point Likert: Intensity
Family Dysfunction (FAM)	Family fights a lot	536	5-point Likert Scale: Agree
	Family throws things	536	5-point Likert Scale: Agree
	Family calmly discusses problems[b]	536	5-point Likert Scale: Agree
	Family criticizes each other	536	5-point Likert Scale: Agree
	Family hits each other	536	5-point Likert Scale: Agree
Neighborhood Quality (NHOOD)	Length of residence[b]	673	4 category: Length of stay
	Place to raise kids	673	5-point Likert Scale: Rating
	Difficulty identifying strangers	671	3-point Likert Scale: Difficulty
	Neighbor report: selling drugs	663	4-point Likert Scale: Likelihood
	Neighbor report: kids in trouble	667	4-point Likert Scale: Likelihood
	Neighbor report: disrespectful child	665	4-point Likert Scale: Likelihood
	Neighbor report: child stealing	664	4-point Likert Scale: Likelihood
	Safe to walk around after dark	671	4-point Likert Scale: safety
School Safety (SCH)	Student physical conflicts [d]	673	Dichotomous
	Robbery or theft[d]	671	Dichotomous
	Vandalism of school property[d]	676	Dichotomous
	Student alcohol use[d]	669	Dichotomous
	Student drug use[d]	668	Dichotomous
	Student weapon possession[d]	676	Dichotomous
	Physical abuse of teachers[d]	679	Dichotomous
	Verbal abuse of teachers[d]	677	Dichotomous

Notes: * All N values from weighted data. Values rounded to nearest whole person for interpretability. [a] Collected from demographic information. [b] Score reversed for conceptual coherence. [c] Reported by the PSID staff member who completed a home interview with the primary caregiver. [d] Collapsed from 3 categories to presence/absence binary.

Cognitive outcomes were measured using three childhood assessments available in the PSID-CDS II. These indicators included tests of reading, mathematics, and memory. Broad reading and applied problem solving scores from the Woodcock-Johnson Psycho-Educational Battery-Revised were utilized (Woodcock & Johnson, 1989). These assessments are widely used and were included in all waves of the PSID-CDS. Additionally, cognitive outcomes were measured using the Wechsler Intelligence Scale for Children (WISC) - Revised Digit Span Test for Short Term Memory (Wechsler, 1974). This test asks students to repeat lists of numbers in forward and reverse directions, and is a widely used test of memory. Table 4.3 provides descriptive statistics for the sample on these three measures. The latent outcome variable was constructed using the age-standardized scores of all these measures.

Table 4.3
Cognitive outcome variables

Test	N	Mean	Standard Deviation
Woodcock Johnson: Applied Problems	650	107.71	17.542
Woodcock Johnson: Broad Reading	606	108.73	15.533
WISC: Digit Span	647	12.32	3.549

Note: All values based on weighted data.

Control variables for these models included a composite measure of socioeconomic status (SES), gender, and race. These demographic factors have previously been shown to be related to cognitive outcomes and school security (Altonji & Mansfield, 2011; Bachman et al., 2011; Hong & Eamon, 2012). The SES variable was constructed from indicators of household income, educational level of the head of household, and occupational prestige of the head of household (O. D. Duncan, Featherman, & Duncan, 1972). The occupational prestige score was determined by cross referencing the values calculated by Hauser and Warren (1996) based on the 1980 census code of the occupation with the occupation for the head of household in the PSID core data. The three SES measures were standardized and the standardized values were summed to create a continuous scale for SES. The binary indicator of gender was taken from the PSID-CDS II data. The race variable collapsed the race and ethnicity identification indicator into a binary indicator of White non-Hispanic and Person of Color identities, due to similarities in achievement gaps between whites and different communities of color (Todd & Wolpin, 2007). This provided an interpretable split and maintained group size for analysis. These variables were used at different stages in the analysis to control for demographic effects.

Analysis

The analysis consisted of three stages. First, a confirmatory factor analysis (CFA) was performed with the individual latent variables using the PSID-CDS Education 2002 sample to demonstrate the relative viability for their continued use in modeling. Second, path models relating the latent and control variables to the outcomes were constructed based on interpretations of the bioecological theory of development and tested using structural equation modeling (SEM). Finally, the sample was divided based on levels of ACEs and the groups were modeled individually using the viable path models. This was done by saving the ACEs factor score and analyzing a frequency distribution of the scores for a theoretically tenable split. All analyses were performed with MPlus 7 (Muthén & Muthén, 1998) using the weighted least squares means and variances (WLSMV) method of estimation, due to the presence of categorical variables as indicators. CFA analyses were evaluated on the ability of the model to recreate the relationships present in the data, as indicated by the root mean square error of approximation (RMSEA), the comparative fit index (CFI) and the Tucker-Lewis index (TLI) (Bentler, 1990; Brown, 2015; Hu & Bentler, 1999). Standardized path coefficients from the SEM models were evaluated based on a standard $p < .05$ level of statistical significance.

Figure 4.1 presents the structure of the latent measures of ACEs, family conflict, neighborhood quality, and school safety. The ACEs measure consisted of 11 indicators gathered under one latent factor. The residual error for the six indicators of primary caregiver emotional distress were allowed to covary to allow for methodological effects, as they were part of the same sub-scale (Brown, 2015). Prior experimentation with this approach to ACEs modeling with the PSID-CDS II has been shown to be acceptable (Olofson, 2017a, 2017b). The family conflict latent variable consisted of five indicators with no correlated residuals. The neighborhood quality latent variable consisted of eight indicators; residual covariance was specified for the two indicators related to neighborhood cohesion, the two indicators of neighborhood safety, and the four variables of neighborhood social norms. The eight indicators of school safety were gathered into one latent variable. Finally, cognitive outcomes were also modeled as a latent variable, using the three cognitive outcome variables. Factor loadings, fit statistics, and correlations among the latent variables were measured using a CFA that simultaneously modeled all latent factors.

Structural equation modeling is group of statistical procedures that allow theory-based hypothesized relationships between observed and latent variables to be tested with non-experimental data (Kline, 2015; Pearl, 2012). The SEM stage of the analysis began with regressing the outcomes on the variables of ACEs, family conflict, neighborhood quality, and school safety individually and then simultaneously. This was done to demonstrate an unmediated relationship between the variables of interest. These models are presented in Figure 4.2 and Figure 4.3, with Figure 4.3. It was hypothesized that increases in ACEs, family conflict, and problems with neighborhood quality and school security would be associated with decreases in cognitive outcomes (Brooks-Gunn et al., 1993; Cook et al., 2010; Forehand et al., 1998; Jaffee & Maikovich-Fong, 2011). Next, the variables were modeled using increasingly complex and theoretically-driven relationships consistent with bioecological development research (Bronfenbrenner & Morris, 2006). As shown in Figure 4.4, school safety, family conflict, and neighborhood quality were modeled as contextual factors influencing outcomes indirectly though the individual as measured by ACEs (solid and dotted paths). Results from prior analyses with this data set indicate the viability of these indirect pathways and the spurious nature of direct pathways from neighborhood quality and family conflict to these cognitive outcomes (Olofson, 2017b). Additional approaches modeled a direct relationship between school safety and cognitive outcomes separate from the ACEs path (solid and dashed paths) and a combined direct and indirect pathway from schools to outcomes (solid, dashed, and dotted paths).

The second research question inquires as to the differences in the function of schools for students with different levels of adversity. Although recent advances in theory and software have enabled the inclusion of interaction effects in some structural analyses (Kline, 2015; Maslowsky, Jager, & Hemken, 2015), the presence of categorical data and the subsequent utilization of the WLSMV estimator preclude the use of such methods in this analysis (Muthén & Muthén, 1998). Instead, the sample was divided into groups based on factor scores on the ACEs latent variable. Factor scores were saved as output from the CFA with the ACEs latent variable and the frequency distribution was constructed. Based on properties of the distribution the groups were constructed and modeled using the approaches containing direct pathways from the school safety variable to the cognitive outcomes (Figure 4.4). Given non-uniform distribution of categorical data over the two groups, i.e., the pattern of category population was not identical in the lower and higher ACEs groups, simultaneous analysis that would allow for direct model comparison as proscribed by Vandenberg and Lance (2000) was not possible. Rather, the significance and magnitude of the standardized path coefficients from the individual group analyses were compared to provide empirical evidence of the nature of school safety as a resource or protective factor.

Results

This section presents the results from the three stages of the analyses. First, the results from the confirmatory factor analysis are presented to demonstrate the fitness of the latent variables. The second section contains the results from the SEM analyses that tested different pathways and relationships among the variables of interest. Finally, the results comparing the students from highly adverse background to those from lower adversity backgrounds are described.

CFA

The structure of the individual latent variables was tested using a CFA approach with the PSID-CDS Education 2002 sample. The latent variables were modeled simultaneously with the data. This allowed for the determination of the factor loadings along with the covariance of the factors. A simultaneous test of the fit for the latent factors is more rigorous than a factor by factor approach, and allows for inclusion of more pieces of information in the determination of factor loadings and overall fit (B. Thompson, 2004) Overall, these results from the CFA indicated excellent model fit: χ^2 = 914.269, df = 527, p < .05; RMSEA = .033; RMSEA 90% C.I. = .029 - .036; CFI = .931; TLI = .922. It should be noted that the chi-squared value inflates with sample size, and so the statistical significance of the value does not provide strong enough evidence for the misfit of the model. The RMSEA was below the cutoff of .05 indicating excellent model fit (Brown, 2015; Hu & Bentler, 1999), and the CFI and TLI were above the threshold of .90 indicating good or acceptable fit (Bentler, 1990). As presented in Table 4.4, the factor loadings for nearly all of the individual indicators were significant at the p < .05 level, and most factor loadings were above the λ > 0.3 level indicating a salient factor loading (Brown, 2015). Given the prior robustness demonstrated by the latent factor for ACEs, family conflict, and neighborhood quality using PSID-CDS data, the overall fit of the model, the utility of these variables in bioecological modeling (Olofson, 2017a, 2017b), and the unified conceptualization in both the instrument and the literature, all indicators were retained for further work.

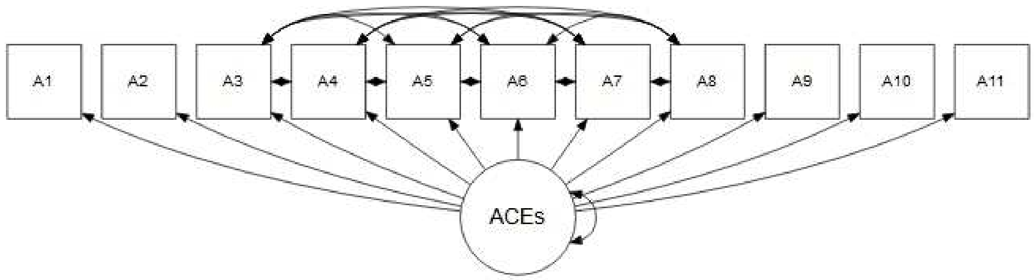

Figure 4.1a

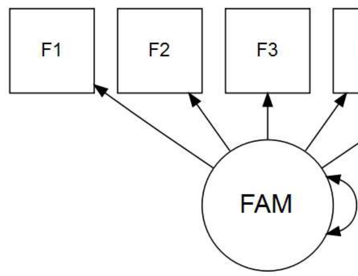

Figure 4.1b

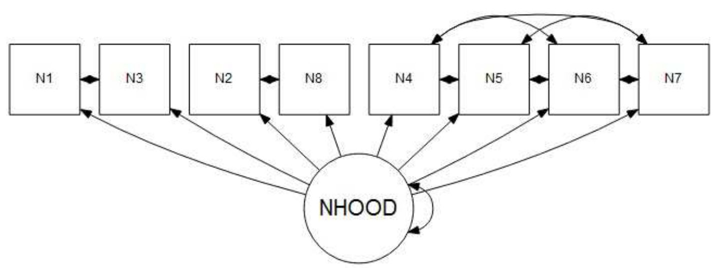

Figure 4.1c

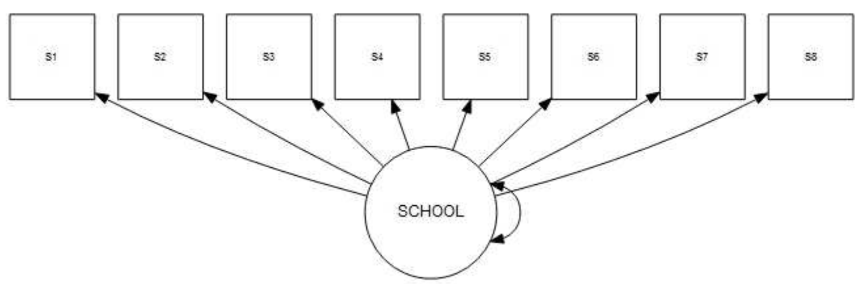

Figure 3.1d

Figure 4.1: Latent variable models for ACEs, family conflict, neighborhood quality, and school security. The loadings and fit statistics for these measurement models are presented in Table 4.4.

Table 4.4
Factor loadings, standard errors, and communalities from CFA results

Latent Variable	Indicator	Factor Loading	Standard Error	Communality	Standard Error
ACEs	A1: Biological parents	.368*	.073	.136*	.054
	A2: Alcohol use	.139	.098	.019	.027
	A3: Nervous	.340*	.059	.116*	.040
	A4: Hopeless	.575*	.071	.331*	.082
	A5: Restless	.348*	.056	.121*	.039
	A6: Effort	.359*	.066	.129*	.048
	A7: Sad	.531*	.072	.281*	.077
	A8: Worthless	.567*	.089	.321*	.100
	A9: Physical affection	.143*	.055	.021	.016
	A10: Hostility	.569*	.051	.323*	.058
	A11: Warmth	.538*	.053	.289*	.057
FAM	F1: Fight	.789*	.033	.623*	.052
	F2: Throw	.806*	.041	.650*	.065
	F3: Calm	.394*	.049	.155*	.039
	F4: Criticize	.613*	.045	.376*	.055
	F5: Hit	.601*	.053	.361*	.064
NHOOD	N1: Length of residence	.115	.067	.013	.015
	N2: Place to raise kids	.880*	.074	.774*	.130
	N3: Strangers	.532*	.057	.283*	.060
	N4: Selling drugs	.305*	.060	.093*	.037
	N5: Kids in trouble	.396*	.058	.157*	.046
	N6: Disrespectful child	.305*	.062	.093*	.038
	N7: Child stealing	.397*	.061	.158*	.048
	N8: Safe after dark	.665*	.092	.443*	.122
SCH	S1: Fights	.737*	.035	.543*	.051
	S2: Theft	.687*	.047	.472*	.064
	S3: Vandalism	.778*	.047	.606*	.072
	S4: Alcohol use	.521*	.091	.272*	.095
	S5: Drug use	.769*	.088	.591*	.136
	S6: Weapons	.723*	.059	.523*	.086
	S7: Physical abuse	.751*	.047	.564*	.070
	S8: Verbal abuse	.845*	.031	.714*	.053
COG	C1: Applied Problems	.846*	.049	.543*	.063
	C2: Broad Reading	.737*	.043	.715*	.082
	C3: WISC	.499*	.062	.249*	.062

Notes: Standardized values shown. * indicates $p < .05$. $\chi^2 = 914.269$, $df = 527$, $p < .05$; RMSEA = .033; RMSEA 90% C.I. = .029 - .036; CFI = .931; TLI = .922.

The correlations between the latent variables are presented in Table 4.5. The latent variables of ACEs, family conflict, and neighborhood quality are moderately to highly correlated. Consistent with prior research concerning ACEs, neighborhoods, and schools, these latent variables were negatively correlated with cognitive outcomes. These results indicate the feasibility of the latent variables as constructed for use in structural models.

Table 4.5:
Variable correlations

	ACEs	*FAM*	*NHOOD*	*SCH*	*SES*	*Female*	*Race*	*COG*
ACEs	1							
FAM	.625*	1						
NHOOD	.595*	.422*	1					
SCH	.275*	.115	.312*	1				
SES	-.581*	-.185*	-.382*	-.255*	1			
Female	.024	-.029	.008	.042	.004	1		
Race	.513*	-.015	.346*	.373*	-.493*	.079	1	
COG	-.427*	-.080	-.289*	-.215*	.434*	.032	-.330*	1

Note: * indicates $p < .05$

SEM

In order to demonstrate direct relationships between cognitive outcomes and ACEs, family conflict, neighborhood quality, and school safety, the outcome latent variable was regressed on each exogenous latent variable individually. These first models were also tested with the inclusion of the control regressors of SES, gender, and race. The results from these models are presented in Table 4.6. The standardized path coefficients for ACEs, neighborhood quality, and school safety in the non-control models were consistently negative and significant. The coefficient for the model regressing cognitive outcomes on family conflict was negative but not significant at the $p < .05$ level. When the control variables were added to the models, the values of the standardized path coefficients were smaller in magnitude when compared to the models without control variables. Additionally, the standardized path coefficient from the school safety latent variable to the outcomes did not maintain statistical significance at the $p < .05$ level, while the coefficients associated with ACEs and neighborhood quality did. The coefficients for the paths from SES to cognitive outcomes and race to cognitive outcomes were consistently significant at the $p < .05$ level for all models. With the exception of the family quality variable, these results indicated that as the traumatic or deleterious nature of these latent variables increased, cognitive outcomes decreased.

Table 4.6:

Cognitive outcome latent variable on individual latent predictors (Figure 4.2)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
ACEs	-.405*	-.236*						
FAM			-.071	-.015				
NHOOD					-.290 *	-.145*		
SCH							-.207*	-.094
SES		.237*		.328*		.291*		.321*
Female		.039		.039		.040		.040
Person of Color		-.259*		-.259*		-.260*		-.260*
Communality								
R^2	.164*	.223*	.005	.177*	.084*	.198*	.043	.187
Fit Statistics								
RMSEA	.049	.062	.048	.059	.026	.054	.050	.060
CFI	.965	.903	.966	.907	.995	.962	.923	.854
TLI	.948	.872	.949	.880	.992	.949	.902	.825

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

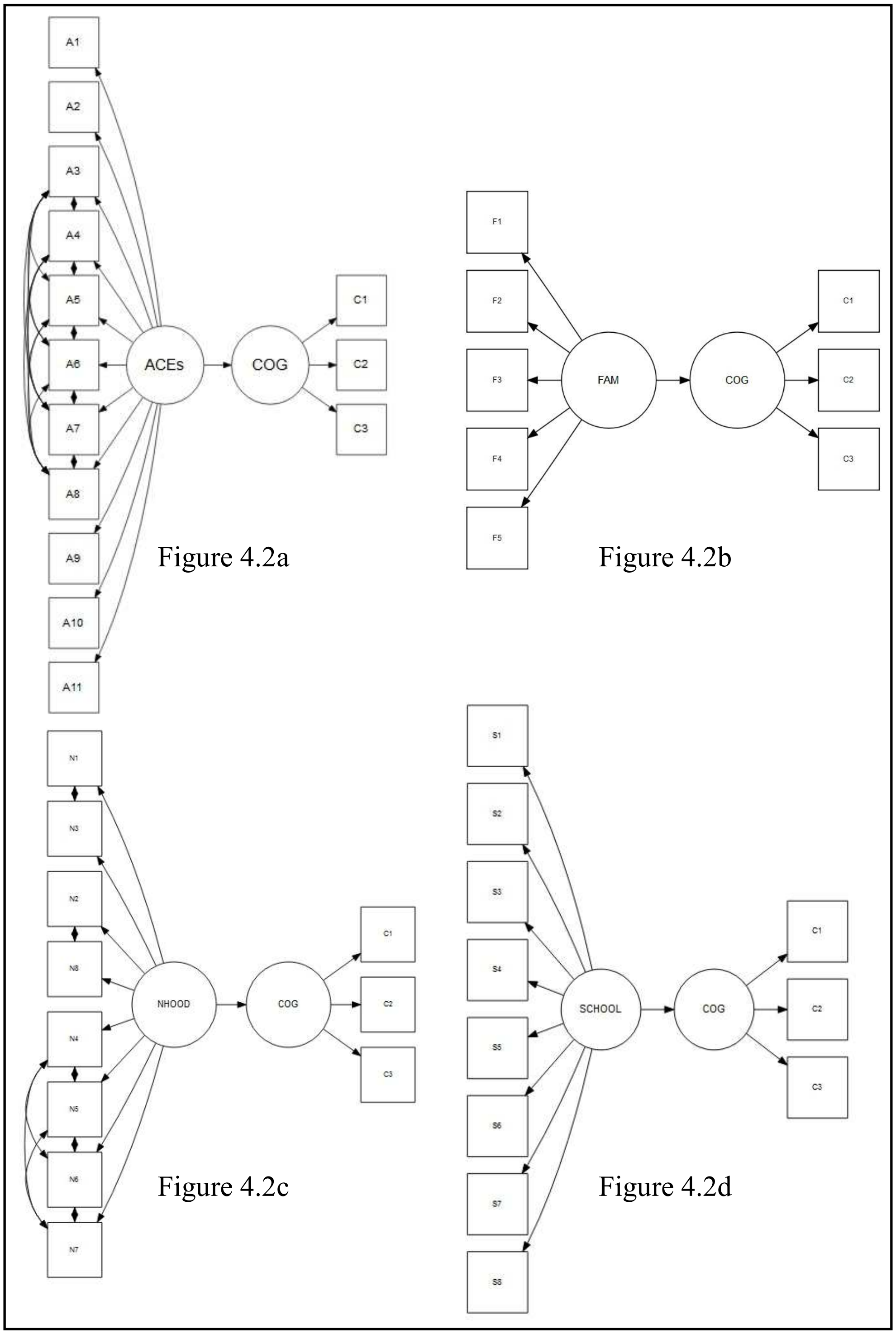

Figure 4.2: Individual path models from exogenous measures to cognitive outcomes. The path coefficients from these models are available in Table 4.6. Control variables of SES, gender, and race are suppressed for clarity.

Following the analyses to observe individual effects, the cognitive outcome latent variable was regressed upon the four exogenous latent variables simultaneously. This model is visualized in Figure 4.3. The results from this analysis are presented in Table 4.7. Again, the standardized path coefficient from ACEs to the cognitive outcomes was negative and significant ($p < .05$) in models with and without demographic control variables. However, the path coefficients from the indicators of family conflict, neighborhood quality, and school safety to cognitive outcomes failed to reach statistical significance in the model that included control variables. This was not surprising given the lack of alignment between this modeling approach and the bioecological model.

Table 4.7:
Cognitive outcome latent variable on all latent predictors (Figure 4.3)

Variable	Model 9	Model 10
ACEs	-.537*	-.460*
FAM	.318*	.294
NHOOD	-.059	-.040
SCH	-.085	-.067
SES		.159*
Female		.039
Person of Color		-.260*
Covariance		
ACEs with FAM	.636*	.688*
ACEs with NHOOD	.598*	.557*
FAM with NHOOD	.424*	.436*
SCH with ACEs	.236*	.144
SCH with FAM	.102	.106
SCH with NHOOD	.271*	.199*
Communality		
R^2	.252*	.281*
Fit Statistics		
RMSEA	.032	.035
CFI	.933	.905
TLI	.924	.894

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

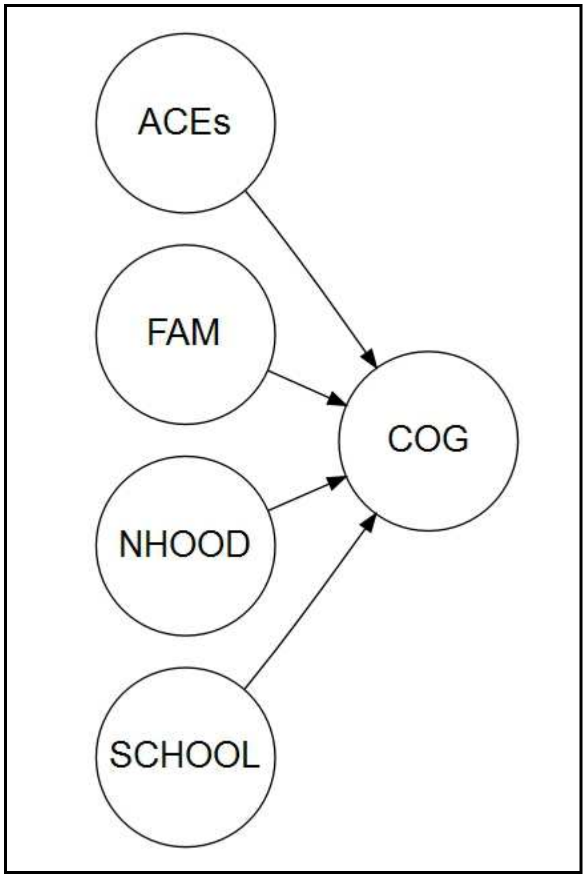

Figure 4.3: Structural model with cognitive outcomes regressed on all contextual latent variables and ACEs. The path coefficients from this model are available in Table 4.7. Control variables and individual indicator variables are suppressed for clarity.

The next modeling approach provided individual paths from family conflict, neighborhood quality, and school safety, through the individual as modeled by ACEs, to the cognitive outcomes. Previous work with these variables and the full PSID-CDS II data set has shown this to be a tenable approach; paths of the family conflict and neighborhood quality variables through ACEs to cognitive outcomes are more defensible than direct paths from these variables to the outcomes (Olofson, 2017b). This model is visualized in Figure 4.4 (solid and dotted paths), and the results are presented in Table 4.8. Although the indirect effects of the family conflict and neighborhood quality variables are negative and significant ($p < .05$) with respect to cognitive outcomes, the pathway from the school safety variable through ACEs to cognitive outcomes is not. This provides evidence that school safety does not occupy the same theoretical position in the bioecological framework as the microsystems of families and neighborhoods in this sample.

Table 4.8
Cognitive outcome latent variable on ACEs; ACEs on family conflict, neighborhood quality, and school safety (Figure 4.4, solid and dotted paths)

Variable	Model 11	Model 12
COG on ACES	-.405*	-.219*
ACEs on FAM	.393*	.487*
ACEs on NHOOD	.408*	.384*
ACEs on SCH	.122	.039
SES		.279*
Female		.039
Person of Color		-.260*
Indirect Effects		
COG→ACEs→FAM	-.159*	-.106*
COG→ACEs→NHOOD	-.165*	-.084*
COG→ACEs→SCH	-.049	-.009
Communality		
R^2 (COG)	.164*	.222*
R^2 (ACES)	.509*	.556*
Fit Statistics		
RMSEA	.032	.035
CFI	.932	.903
TLI	.924	.893

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

Rather than modeling only indirect effects of school safety to cognitive outcomes, the relationship was modeled as a direct effect (dashed path) and as both a direct and indirect effect (dashed and dotted path), in conjunction with the previously established indirect pathways from family conflict and neighborhood quality, though ACEs, to cognitive outcomes. The results from the model with only a direct effect for school safety are presented in Table 4.9; the results from the model with a direct and indirect effect for school safety are presented in Table 4.10. In both models the standardized path coefficient for the direct path from both ACEs and school safety to cognitive outcomes is negative and significant at the $p < .05$ level. The standardized path coefficients from family conflict and neighborhood quality to ACEs are positive and significant ($p < .05$) in both models, and the indirect pathways from family conflict and neighborhood quality to cognitive outcomes are negative and significant ($p < .05$). However, the indirect pathway from school safety through ACEs to cognitive outcomes in the final model is marginal in size and not significant ($p > .05$). These results indicate a direct, rather than indirect, relationship between school safety and cognitive outcomes when indicators of adversity, family conflict, and neighborhood quality are modeled as guided by the bioecological framework.

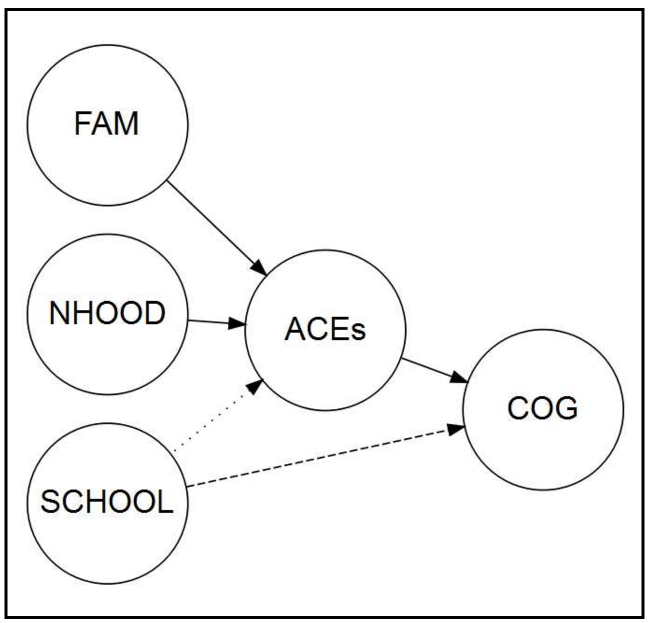

Figure 4.4: Structural model with cognitive outcomes regressed on ACEs, ACEs regressed on family conflict and neighborhood quality latent variables, and intermittent paths from school safety. The path coefficients from this model are available in Tables 4.8, 4.9, and 4.10. Control variables and individual indicator variables are suppressed for clarity.

Table 4.9:
Cognitive outcome latent variable on ACEs and school safety; ACEs on family conflict, neighborhood quality; comparison of high and low ACE groups (Figure 4.4, solid and dashed paths)

Variable	Model 13	Low ACEs	High ACEs
COG on ACES	-.346*	-.339*	-.536*
COG on SCH	-.146*	-.221*	-.087
ACEs on FAM	.394*	.402*	.459*
ACEs on NHOOD	.453*	.460*	.096
Indirect Effects			
COG→ACEs→FAM	-.136*	-.136*	-.246*
COG→ACEs→NHOOD	-.157*	-.156*	-.052
Communality			
R^2 (COG)	.159*	.151*	.315*
R^2 (ACES)	.511*	.514*	.268*
Fit Statistics			
RMSEA	.031	.041	.034
CFI	.933	.886	.927
TLI	.925	.873	.918

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

Table 4.10:
Cognitive outcome latent variable on ACEs and school safety; ACEs on family conflict, neighborhood quality, and school safety; comparison of high and low ACE groups. (Figure 4.4, all paths)

Variable	Model 13	Low ACEs	High ACEs
COG on ACES	-.348*	-.358*	-.496*
COG on SCH	-.133*	-.250*	-.173
ACEs on FAM	.409*	.331*	.603*
ACEs on NHOOD	.403*	.472*	.192
ACEs on SCH	.085	-.126	-.341
Indirect Effects			
COG→ACEs→FAM	-.142*	-.118*	-.299*
COG→ACEs→NHOOD	-.140*	-.169*	-.095
COG→ACEs→SCH	-.030	.045	.169
Communality			
R^2 (COG)	.160*	.159*	.278*
R^2 (ACES)	.502*	.483*	.401*
Fit Statistics			
RMSEA	.032	.041	.034
CFI	.932	.887	.929
TLI	.924	.873	.920

Notes: Values are standardized path coefficients. * indicates $p < 0.05$.

Group Comparisons

In order to create comparable groups based on ACEs prevalence, a frequency distribution of the factor score of the ACEs latent variable for the sample was constructed. Visual inspection of this distribution indicated a tri-modal structure, corresponding with low, medium, and high values for ACEs. Given the binary nature of the research question, the elevated relationship between high levels of ACEs and problems in school (Bethell et al., 2014; Center for Promise, 2015), and some key variables holding a constant value in the low ACEs group, the low and medium groups were combined and compared to the high ACEs group. The low-to-medium group consisted of 69.8% of the original PSID-CDS Education 2002 sample, with 30.2% of the original sample being identified in the high group. A binary variable indicating group membership was constructed to segregate groups in further analyses. It should be noted that a parallel analysis was conducted using the median score as a cut point to generate groups; results from these analyses were not qualitatively different.

The low-to-medium and high ACEs groups were modeled individually using the model that provided a direct pathway from the school safety latent variable to the cognitive outcomes. The results from these analyses are presented in Table 4.9. In the low-to-medium ACEs group, the standardized path coefficient from school safety to cognitive outcomes was negative and significant ($p < .05$). However, in the high ACEs group, the value of the same path coefficient was marginal and not significant ($p > .05$). Additionally, the direct path from neighborhood quality to ACEs and the indirect path from neighborhood quality through ACEs to cognitive outcomes were marginal and not significant ($p > .05$) in the low-to-medium ACEs group. The groups were also analyzed using the model that included direct and indirect pathways from school safety to cognitive outcomes. Similarly, for the low-to-medium ACEs group the standardized path coefficient was negative and significant at the $p < .05$ level, while in the high ACEs group the coefficient did not reach statistical significance ($p > .05$). Similar to the analysis with the full sample, the indirect pathway from school safety through ACEs to cognitive outcomes was marginal and not statistically significant ($p > .05$) for both low-to-medium and high ACEs groups. These results indicate that in the low ACEs group, as problems with school safety increase, cognitive outcomes decrease; however, such a relationship was not found in the high ACEs group.

Discussion

The purpose of this study was to model the relationship between school security and cognitive outcomes for pre- and young adolescents while employing multiple developmental influences. SEM was used in order to parse out the nature of the relationship among school safety, childhood adversity, and the contextual influences of neighborhood quality and family conflict. As shown in the model described in Figure 4.2d, in a direct model, as problems related to school safety increased, cognitive outcomes decreased. These findings align with research investigating the relationship between negative school environments and academic outcomes (Cook et al., 2010).When school safety is conceptualized as functioning through the individual as modeled by ACEs, along with family conflict and neighborhood quality, the indirect relationship between schools and cognitive outcomes was not observed. Rather, as shown in Figure 4.4, it was only when school safety was modeled with a direct pathway to cognitive outcomes that the standardized path coefficient remained statistically significant. This demonstrates that although the contextual elements of families and neighborhoods can be conceptualized as functioning through the individual as measured by adversity (Olofson, 2017b), the function of school safety has a direct, rather than an indirect, relationship with cognitive outcomes. Although common conceptualizations of the bioecological model group schools as microsystems in parallel with families and neighborhoods (e.g., Berns, 2010), the findings from this study indicate differences in the paths of the developmental impact of these proximal systems.

The results indicate that an overall improvement in the school environment would benefit students generally. As found by Voight and Hanson (2017), increases in the quality of school climate help to support increases in academic performance. In order to bring about improved school safety, both structures, such as clear rules and procedures for reporting violence, and support, such as seeking and providing help for victims, are necessary (Gregory, Cornell, & Fan, 2012). Vitally, principals need to take a central role in promoting and maintaining school safety (Astor, Benbenishty, & Estrada, 2009). Based on their reading of the middle school safety and climate literature, Juvonen and colleagues (2004) suggest that *"[p]rincipals and teachers of early teens need to adopt comprehensive prevention models (for example, schoolwide antibullying programs) that focus on changing the social norms or the peer culture that fosters antisocial behavior"* (p. 117, emphasis in original). Such programming could address problematic school safety, which, in this study and elsewhere (e.g., Cook et al., 2010; Voight & Hanson, 2017), has been found to negatively predict cognitive outcomes in general.

Although these models indicate the potential for increases in school safety to support achievement, the effect sizes were relatively small. Improving school safety by a full standard deviation is only associated with a shift in less than one sixth of a standard deviation in the outcomes. Given that the school safety variable consists of numerous binary indicators, this would mean a substantial shift in the school climate, as numerous problems would have to be identified and resolved in order to shift the value of the latent variable. However, small improvements in developmental conditions early in life course development can have positive effects that "cascade" and amplify as a child continues to develop (Masten & Cicchetti, 2010). From this perspective, such efforts to make changes in school safety may be a worthwhile investment.

Consistently across the model in this study, as ACEs increased, cognitive outcomes significantly decreased. This relationship over time creates an achievement gap between students with high and low adversity. The second research question investigated the influence of school safety on cognitive outcomes for students from high and low adversity groups. As the results in Tables 4.9 and 4.10 show, increases in negative indicators of school safety co-occurred with decreases in cognitive outcomes for students at lower adversity levels. For students at higher adversity levels, this relationship was not apparent. Neither the direct nor the indirect pathways from school safety to cognitive outcomes were found to be statistically significant. This indicates that, when modeled in conjunction with contextual measures of neighborhood quality and family conflict, the relationship between school safety and cognitive outcomes is different for students from high and lower adversity groups. An increase in problems with school safety is impactful on cognitive outcomes for students with less adversity; for students from high adversity backgrounds, the levels of school safety are not a meaningful predictor of cognitive outcomes.

The findings from this study support the notion that improvements in school security ought not be considered a "protective factor" (Conrad & Hammen, 1993; Hammen, 2003) with respect to children from high adversity backgrounds. As found by Herrenkohl and colleagues (2009), improvements in school climate do not provide a significant mediating effect on the relationship between contextual variables and adult outcomes for students from adverse upbringings. With regard to graduate rates, although improvements and supports in school can help students with low or medium-range ACEs, for students with high rates of adversity, "social support does little to buffer the effects of adversity; the hurdles are too high for support alone to keep students in school" (Center for Promise, 2015, p. 23). This study adds to these previous findings by providing evidence of the inability for changes in the school environment alone to be enough to induce positive changes student cognitive outcomes in pre- and early adolescence, preceding high school or adult outcomes.

This conclusion supports the notion that in order to bring about increases in academic achievement, educational policy needs to be more broadly conceived (Anyon, 2005). Schools can support the cognitive development of children only to an extent. Improvements in schools cannot undo the deleterious effects of other developmentally important contexts. In order to create structures and supports for children, packages of policies could be used to target inequities in these different contexts, and the resulting conditions be used as feedback to further craft and shape policy (Snyder, 2013). Such packages would necessarily support multiple facets of a child's context: not just schools, but families and neighborhoods as well.

There are a number of conditions that limit the generalizability of this study. Although the PSID-CDS II is a nationally representative sample, the constituency of the sub-sample used in the models was determined by the presence of responses from the elementary teachers. There is not enough information provided in the PSID-CDS about these teachers to determine potential bias in the response rate. Additionally, the limitations to the sample size along with the use of categorical data disallowed tests of group invariance across the high and low ACEs groups. The total available categories were not represented identically across the two groups, making tests of structural invariance impossible (Vandenberg & Lance, 2000). The relationships between the latent variables cannot be assumed to be identical across the groups. Without such an indication, model misspecification for some groups at the level of these latent variables cannot be ruled out, and that results from the subsequent SEM cannot be considered indicative of the relationships among these variables across demographic groups. However, although these conditions limit the application of the findings, they remain illustrative and useful for the framing of additional studies.

Subsequent research into the relationships between school security and childhood adversity could utilize a larger sample of young people to better tease out these relationships. For example, the Childhood Retrospective Circumstances Supplement (CRCS) to the PSID contains numerous variables that are analogous to those used in this study, with over ten times as many participants. Such an analysis would continue to allow for intersections with the PSID core data. In addition to the SEM approach, other methodologies could be used to illuminate the relationships between ACEs, schools, and cognitive outcomes. As demonstrated by the Center for Promise (2015), latent class analysis can be used to create classes of children wherein the level of ACEs is but one dimension. An appropriate data set with a younger sample could further add to the understanding of effects on the precursors to high school graduation, such as the cognitive outcomes modeled in this study. Finally, qualitative work could be conducted to better understand differences and similarities in the ways that students from low and high adversity backgrounds relate to school, to better hone variable selection and modeling techniques.

Conclusion

Schools are an important factor in the cognitive development of pre- and young adolescents (Eccles & Roeser, 2011). Children with higher levels of adversity face challenges to their cognitive development (Hindman et al., 2010). Interventions in areas that support children with higher levels of adversity can be used to help close gaps between children with high adversity and low adversity (G. J. Duncan & Murnane, 2014). This study investigated school safety as a potential area for intervention. If safer schools corresponded to better cognitive outcomes for children from more adverse background in particular, then reforms to enhance school safety could be used to elevate children with higher adversity. However, rather then functioning as a protective factor, changes in school safety served to support the cognitive outcomes of all children. Although safer schools are beneficial for all students, more broad social change is necessary in order to undo the effects of adversity early in the lives of children.

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CHAPTER 5

Conclusion

Early childhood adversity has consistent negative repercussions that often resonate throughout an individual's life (Center for Disease Control and Prevention, 2015; Dong et al., 2005; Felitti et al., 1998; Felitti & Anda, 2010). This early childhood adversity has negative impacts not only on a child's potential, but also their cognitive and socio-emotional development in childhood and adolescence (Brooks-Gunn & Duncan, 1997; G. J. Duncan & Murnane, 2011; Jaffee & Maikovich-Fong, 2011; Marie-Mitchell & O'Connor, 2013; Thompson et al., 2015). The purpose of the three research endeavors presented in this dissertation was to create a model relating childhood adversity, family conflict, neighborhood quality, school safety, and cognitive outcomes in order to better understand the relationships among these constructs. The resulting models allowed for the observation of these relationships and the testing of different theoretically driven propositions and assumptions. Additionally, the process of creating and evaluating models generated suggestions for methodological approaches and additional utility for the utilized data set. Results further elaborated on the theoretical model, and provided numerous implications for practitioners and researchers. Taken together, these three studies represent a contribution to the ongoing process of understanding and modeling childhood adversity as part of a complex system of influences on development, in which schools and educators play a major role.

These studies were driven by three sets of research questions. The first study addressed the following research questions:

1) Is a theoretically-constructed latent measurement model for adverse childhood experiences (ACEs) able to reproduce the relationships between variables present in the PSID-CDS data?
2) Is this measurement generalizable across groups classified by race, gender, and age?

The findings indicate that the measurement model, which followed the original framework set out by Felitti and colleagues (1998), represents an excellent fit for the data. Moreover, the latent-variable approach wherein the individual indicators retained their variance and were allowed to make independent contributions to the central ACEs measures were a better representation of the relationships in the data than widely-used cumulative risk approaches (Evans et al., 2013). Further investigation of the invariance of the model across demographic groups indicated that this approach was suitable for gendered groups, but was not suitable for application across racial or age-level groups. However, rather than direct evidence for the unsuitability of the model for racial or age groups, this finding stemmed from a lack of symmetry in the categories of responses that were selected across the groups, which disallowed further investigation following widely-utilized guidelines (Vandenberg & Lance, 2000).

The resulting one-factor model was used in the second study, which addressed the following research questions:

3) When modeled using ACEs, family conflict, and neighborhood quality, what is the nature of the path coefficients from the individual, families, and neighborhoods to cognitive outcomes?

4) Are the relationships between the family and neighborhood contexts and cognitive outcomes better modeled as a direct pathway or as indirect pathways through the individual as measured by ACEs, consistent with the bioecological model of development?

When individually modeled along with controls for socioeconomic status, gender, and race the findings show that as ACEs and family conflict increased, cognitive outcomes decreased. As neighborhood quality increased, cognitive outcomes increased, although this effect was relatively small. These findings mirror the general consensus around these variables and outcomes in childhood and adolescence (Bethell et al., 2014; Eccles & Roeser, 2011; Evans et al., 2008; Forehand et al., 1998; Leventhal & Brooks-Gunn, 2000; Sharkey & Faber, 2014; Thompson et al., 2015). Further investigation using SEM to generate and test paths to the cognitive outcomes indicated that family conflict and neighborhood quality were better modeled as functioning through the individual as measured by ACEs, rather than having direct effects on the outcomes. This reinforces the position of some researchers that such developmental influences cannot be modeled in isolation, and that an understanding of the individual is a necessary precursor to understanding the influence of contextual elements (Bronfenbrenner & Morris, 2006; Darling, 2007).

The third study brought schools into the growing model, and addressed the following research questions:

5) Are increases in the school safety conditions related to cognitive functioning of students in kindergarten to seventh grade when schools are modeled as a microsystem functioning through the individual?

6) Is the relationship between school safety and cognitive outcomes different for students from high adversity backgrounds when compared to students from lower adversity backgrounds?

Results indicated that as problems with school safety increased, cognitive outcomes decreased. Unlike the influence of family conflict and neighborhood quality, this relationship was found to be better modeled as a direct relationship, rather than an indirect relationship functioning through the individual as modeled by ACEs. The negative relationship presented herein is consistent with the literature related to school safety and academic outcomes (Cohen & Geier, 2010; Cook, Gottfredson, & Na, 2010; Osher, Spier, Kendziora, & Cai, 2009; U.S. Department of Education, 2012). By contrast, the relationship was not found to be homogenous when students with high levels of ACEs were compared to those with low to medium levels of ACEs. Here, the relationship between school safety and cognitive outcomes was found to be negative and significant for students with lower levels of ACEs, but the relationship was not found to be significant for students with higher levels of ACEs. This expands the findings of one strand of research that suggests that the effect school environments is “washed out” by highly deleterious developmental conditions outside the school (Altonji & Mansfield, 2011; Center for Promise, 2015; Herrenkohl et al., 2009).

These studies utilize structural equation modeling to construct latent variables and relate them to each other through path models. SEM allows for theory-based modeling and decision making; it also enables the testing of theory-based hypothesized relationships with non-experimental data (Kline, 2015; Pearl, 2012).

SEM worked will for a number of reasons. First, the bioecological model of human development implies complex relationships between the individual and the developmental contexts (Bronfenbrenner, 1994; Bronfenbrenner & Morris, 2006; Darling, 2007). SEM allowed for the construction of complex models and for testing of the presence of direct and indirect relationships via meditational pathways (Cole & Maxwell, 2003; Kline, 2015). Relationships such as the indirect path from family conflict to outcomes and the direct path from school safety to outcomes could be observed with more clarity than regression approaches. Second, the constructs in question – neighborhood quality, family conflict, etc. – could not be directly measured. The use of latent variables allows for the indirect observation of these underlying constructs by using indicator variables (Bollen, 2002). Instead of information loss due to collapsing indicators into indices, the variance in the indicators was maintained. The use of fit indices also clarifies the level to which the theoretical measurements are supported by the relationships present in the real-world data.

The data from the PSID-CDS II was largely well-suited for these studies. The nationally representative nature of the data limits the potential for regionally or demographically specific characteristics to skew results away from the national portraiture (McGonagle et al., 2012). As demonstrated in these studies, the questions present in the data set are highly aligned with a number of developmentally-important contextual constructs. The presence of well-established outcome variables, including Woodcock-Johnson assessments and the WISC assessment for short-term memory, allows for an interpretation of cognitive outcomes that is less tied to the specifics of any particular educational setting. However, although the PSID-CDS II was on the whole useful, the utility of the elementary and middle school teacher module was more limited. With the eligibility of teacher contact determined by parents based on unobserved forces and the rate of missing data approaching 50% (Institute for Social Research, 2010), conclusions based on the data are tenuous. While the findings from the third study, which used this data, are of interest, they may serve better to direct further research with the bioecological framework for development and school safety than to stand on their own.

These studies followed the bioecological model for human development theoretical framework (Bronfenbrenner, 1976, 1996, Bronfenbrenner & Morris, 1998, 2006). The framework guided the determination of variables for inclusion into the models, and the relationships that were tested. An emphasis on proximal influencers led to the inclusion of family conflict, neighborhood quality, and school environment. The consistent use of adversity as a measurement of the individual allowed for the inclusion of the "person at the center of the circles" (Darling, 2007). While the bioecological framework was useful, these studies did not fully engage with the established idea that the relationships between the individual and contextual components are different over time (Sameroff, 2010) or that such relationships are different across socially constructed demographic categories (Garcia Coll et al., 1996). Such considerations constitute one of many potential veins of further research related to these studies.

Future Research

As noted by Thompson and colleagues (2015), the patterns of ACEs through youth and adolescence, and their influence on immediate and long-term outcomes, remains an area ripe for study. Although these studies provide additional findings related to this need, they also lay the groundwork for additional research. First, as noted in the previous section, the pathways and relationships described in these studies can be investigated for differences and similarities across groups sorted by age, race, and gender. The similarities or differences in relationships across these groups would inform our understanding of interactions between development and these constructs. Second, while the bioecological model of human development includes the influence of peers, these studies did not include a measurement of this proximal construct. Further research following many of the same methodological lines can be conducted to incorporate measures of the quality of friendships in childhood, feelings of loneliness, and acute or persistent bullying. Finally, of particular interest to educational researchers, additional measures of the school environment, beyond school safety, could be included to better understand the impact of schools on children from highly adverse backgrounds, and the potential for school-level interventions to support such students.

While some of these research questions may be able to be tackled using the PSID-CDS II, the data set lacks the indicators and sample size to engage with all of these questions. However, the PSID contains a number of other supplements, along with the core PSID data. Additional research is necessary to explore the utility of these additional data sets. Most promising is the Childhood Retrospective Circumstances Supplement (CRCS). This data set contains numerous indicators related to the developmental constructs used in these studies, along with a broad selection of self-reported variables related to childhood adversity. The larger sample size (N = 8076) allows for greater power in testing across demographic groups, and the entirety of the sample has also participated in the larger PSID core survey. In order to operationalize the CRCS in the same way as the PSID-CDS II, a CFA similar to the first of these studies should be conducted to test for the viability of an ACEs measure. Following the identification of a robust measure of ACEs, SEM could be used to investigate questions guided by the bioecological model of human development. Such research activities have the potential of attracting additional funding from the Eunice Kennedy Shriver National Institute of Child Health and Human Development, which supports efforts to expand the utilization of the PSID data sets in the study of childhood development. This type of research has the ability to inform practitioners and policy-makers to create and implement systems and strategies to support healthy children in the US.

Limitations and Demographics Considerations

The approaches to racial, ethnic, and cultural considerations in the models in these papers were limited in their conceptualization and operationalization. The variables used throughout were a gender binary, a racial binary indicating membership to White and Person of Color categories, and a continuous indicator of SES. The selection of these variables introduces a number of assumptions about the individuals in the study. First, the use of a binary indicator of gender not only marginalizes the experiences not only of non-binary individuals, but essentializes the conceptualization of gender and maps it onto a biological sex paradigm. The decision to collapse diverse racial and ethnic groups into one non-White category, while methodologically convenient, potentially masks the diverse experiences of individuals from different groups. Although Todd and Wolpin (2007) used econometric analyses through a human capital theoretical lens to show the similarity of the relationships between a number of regressors and cognitive outcomes across children in non-White groups, from a developmental perspective, such a reductive variable is troublesome. Finally, although the measurement of SES was constituted of inputs beyond simple measures of income or wealth, the SES variable was not interacted with other key demographic indicators to illuminate the potentially different nature of the relationships between SES and cognitive achievement in diverse populations.

In addition to being conceptually limited, the constructs were utilized in limited ways. In the modeling in the first paper, these categories were operationalized by the pursuit of evidence of measurement invariance in the model of ACEs across the groups. Although invariance across gendered groups could be established, such invariance could not be established across the racial groups. Although this limitation was noted, this limitation to generalizability was carried over into the following studies. In the second and third papers, race, gender, and SES were included as control variables, with finalized structural models tested against the inclusion of these variables as regressors with a direct relationship with the cognitive outcome latent variable. These variables were not modeled as having meditating or moderating roles.

The sequestration of these variables to direct relationships with respect to the cognitive outcomes did not incorporate findings from empirical literature that has demonstrated interaction effects between the contextual constructs included in the model and these factors. For example, family conflict has been shown to have different effects on developmental outcomes for children of different genders (Evans, Davies, & DiLillo, 2008). Race and ethnicity has also been shown to have a mediating effect on family conflict (Pachter, Auinger, Palmer, & Weitzman, 2006). Similarly, neighborhood effects have been shown to be different across racial groups (Dong, Gan, & Wang, 2015; Jencks & Mayer, 1990) and gender (Entwisle, Alexander, & Olson, 1994). The intensity of neighborhood influences have also been shown to be more intense at lower levels of SES

(Cleveland, 2003; Harding, Gennetian, Winship, Sanbonmatsu, & Kling, 2011). With regard to school environments and school security, Mester and colleagues (2015) found evidence that feelings of security differ by whether a student is African American or Caucasian. Lacoe (2015) demonstrated that this gap in feeling safe extends to Latino and Asian students as well. Hong and Eamon (2012) found differences in the perception of school security and environment across different genders of students, and perceptions of school safety also differ among students from different socioeconomic levels (Bachman et al., 2011; Tanner-Smith & Fisher, 2016). Limiting models that include these developmental contexts from interacting measures of the contexts with race, gender, and SES inhibits the ability of these models to fully capture the child's development.

This approach also did not heed direction from the strand of theoretical literature regarding race, culture, and contextually based models of development. As laid out by Garcia Coll and colleagues (1996), social position and stratification needs to be at the core, rather than at the periphery of models of development. Children from historically empowered groups and children from historically marginalized groups have different experiences with proximal and distal developmental forces. There are developmental forces that function only for kids of color, and there are developmental forces that function differently for kids of different ethnic and racial groups. For example, African American children are impacted by institutional racism that leads to the creation of segregated neighborhoods. These segregated communities lead to experiences for African American children that they do not share with White children. Experiences with policing in a neighborhood can function differently for children from marginalized groups as they have frequently been victimized by police violence. While the presence of police increases anxiety in these children, for White kids, a police presence in the neighborhood is unlikely to create such anxiety. The larger societal "macrosystems" in the bioecological model are proximal, rather than distal, for kids of color.

As race and other demographic variables are socially constructed, they cannot be disentangled from the other societal elements, particularly when approaches to modeling development center on the impact of the developmental contexts (Garcia Coll et al., 1996). In order to operationalize these theoretical points, a number of approaches could be tried. As demonstrated by Masten and colleagues (2005), in addition to being modeled as regressors with respect to outcomes, indicators of race, ethnicity, or SES can be modeled as regressors with respect to measures of the developmental contexts. This allows for the inspection of the different paths for significance in the model. Under such models, the measures of the constructs could be understood as partially or fully mediating the relationship between the demographic measure and the outcome. Throughout the models in the second and third papers, race and SES were correlated, but not collinear, with measures of ACEs, family conflict, neighborhood quality, and school safety. Interacting these demographic variables with the measures of these contexts could help to further elucidate the role of race, ethnicity, gender, and SES.

Alternative or in addition to this approach, the contexts themselves could be modeled using variables which have been shown to have a larger impact among communities of color than in predominantly White communities. Iterations of the ACEs framework have included the incarceration of one parent, separate from the indicator of both biological parents not being present in the home (Center for Disease Control and Prevention, 2015). Incarceration affects a disproportionate amount of African American families and poor families in the US (Wagner & Sakala, 2017). The exclusion of this variable from the ACEs measurement changes the nature of the measurement, and contributes to the failure of the ACEs measurement to capture the larger range of adverse experiences. Cultural differences in family dynamics and constituencies were not present in the model as constructed. The presence or absence of extended family affects the dynamics of families from different cultures differently (Rivera et al., 2008). Cohesive neighborhoods may help to buffer the effects of institutional racism; measurements of neighborhoods attenuated to capture this may better model the interaction between this proximal system and the distal backdrop of institutionalized racism. Additionally, urban neighborhoods are likely to function differently than suburban or rural neighborhoods. As kids of color are more likely to live in the former (US Census Bureau, 2016), failing to include this element into a measurement of neighborhoods further hides the full experience of kids of color. Finally, additional variables about schools or classrooms are likely necessary for inclusion in order to better capture the experiences of kids of color. For example, the implicit racial bias of teachers, is both poorly studied and potentially has a large impact on kids from non-White populations (Warikoo, Sinclair, Fei, & Jacoby-Senghor, 2016). Numerous modifications to the ways in which these contexts are measured could be more inclusive of these important factors.

While including additional indicators into measures of these contexts could help to better model the contexts in relation to kids of color, such efforts may still fail to capture the impact of racialized experiences over time. As described by Masten and Cicchetti (2010), developmental influences change over time, and an individual's interactions with contexts at a future time are shaped by their prior experiences. A cascading model utilizing lagged effects with these demographic variables functioning at the different time points could potentially model the interplay between these demographic characteristics and the developmental contexts over time. Rather than a fixed effect, these demographic variables could be allowed to function differently at different developmental stages. Extrapolating this lagged effect approach to the larger macrosystem perspective, it could be possible to use the same cascading approach with multi-generational longitudinal data, in order to model the generational transfer of inequality and longitudinal impact of injustice.

These different approaches to modeling would likely fundamentally modify the results found in these three papers, transforming the conclusions and policy recommendations that stem from the findings. This modification highlights potential tensions stemming from models that are dependent on demographic variables. While failing to fully consider race, ethnicity, SES, gender, as developmentally important variables in the construction of models can serve to "whitewash" the experience of diverse groups. Using different models for different groups has the potential to generate different policy solutions for different groups. Such policy solutions may force policymakers to make difficult decisions given limitations in resources. However, without sound developmental research that accurately represents the experiences of individuals from outside of historically privileged groups, debates about resource allocation are limited from their initiation.

Implications

A better understanding of the interconnected influences of childhood adversity, contextual factors, and cognitive outcomes as presented in these studies is useful for educational leaders and teachers. As pointed out in the third study, school principals are central to the effort to improve school safety and climate to support the achievement of all students (Astor, Benbenishty, & Estrada, 2009; Juvonen, Le, Kaganoff, Augustine, & Constant, 2004). More broadly, the literature on effective models of educational leadership for student performance consistently points to building relationships with families and communities as a vital aspect (Hitt & Tucker, 2016). The results from these studies further emphasize the importance of these outside-of-school contexts on academic outcomes; by helping to make strong connections, school leaders can support all students. Similar to leaders, teachers can implement programs that support positive changes to school climate, helping the academic and social lives of all students (Nocera, Whitbread, & Nocera, 2014). The results from these studies can also help teachers to understand the multiple familial and contextual influences on their students, which may manifest as poor academic performance. A more complex perspective of the lives of children could help teachers maintain perspective and understand the limitations of what can be achieved within the school walls.

As argued by Anyon (2005), education policy ought to be broadly conceived if it is to address persistent inequalities. These studies support the notion that the deleterious effects of adversity, family conflict, and dangerous neighborhoods cannot be solely counteracted within the school walls; consequentially, educational policy cannot stop there either. With the educational domain so-conceived as a complex system, packages of policies could be used to target inequities in these different contexts, and the resulting conditions be used as feedback to further craft and shape policy (Snyder, 2013). Although policies aimed as building capacity and changing entire systems are politically tenuous and only able to be evaluated over longer timelines (McDonnell & Elmore, 1991), these studies highlight the necessity of such a large-scale, multi-faceted approach to policy for equitable education.

Finally, the findings from these studies have a number of implications for educational researchers. First, as has become apparent to a number of scholars (e.g., Bethell et al., 2014; Finkelhor, Shattuck, Turner, & Hamby, 2013; Flaherty et al., 2013; Moore & Ramirez, 2015; Stambaugh et al., 2013), numerous existing national data sets contain indicators suitable for ACEs research. The results from this study support the further utilization of the PSID-CDS in these efforts. Second, the results from these studies along with other recent studies using a latent variable approach to studying ACEs (e.g., Ford et al., 2014; Moore & Ramirez, 2015) highlight the relative strengths of the method; researchers of human development ought to consider SEM as an alternative to traditional multivariate regression approaches. Finally, although these different constructs have been demonstrated to interact directly with cognitive outcomes, there is a need to engage with complexity in order to make more true-to-life models, and to better understand the interrelated nature of these contexts. Continuing to generate and test complex models of development will provide a deeper understanding of the developmental conditions that create and exacerbate inequities in educational outcomes.

Such research could continue to better inform those who do the daily work of education, and those who create, enact, and implement the policies that govern our system of education. As demonstrated throughout these studies, simplified relationships between any of these contexts and student outcomes can be modeled and patterns revealed. However, such myopic approaches also lose the wider perspective on how development occurs in the real world. It is only by taking into account the network of influences that we can build a better understanding of student development, and the potential for schools to help support students who come from, and live with, adversity.

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