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Assessing Structural Models of Neighborhood and Family Sociodemographic Characteristics and  
Relations with Externalizing Psychopathology

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An abstract of  
A thesis submitted to the Faculty of the  
James T. Laney School of Graduate Studies of Emory University  
in partial fulfillment of the requirements for the degree of  
Master of Arts  
in Psychology  
2022

## Abstract

### Assessing Structural Models of Neighborhood and Family Sociodemographic Characteristics and Relations with Externalizing Psychopathology

By Christopher D. King

**ABSTRACT:** Externalizing psychopathology in youth includes symptoms of attention-deficit/hyperactivity disorder (ADHD), conduct disorder (CD), and oppositional defiant disorder (ODD). Prior studies of youth externalizing find small associations with neighborhood sociodemographic characteristics and small-to-moderate associations with family sociodemographic characteristics. However, such studies generally use suboptimal operationalizations of neighborhood sociodemographic characteristics and broad externalizing psychopathology. Consequently, the relations between these variables may be misestimated. The current study 1) addresses these limitations with a latent variable modeling approach to characterize more optimal measurement models for externalizing, family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics, and 2) assesses structural relations between these constructs. Using a population-representative, ethnically diverse sample of 2192 twins and siblings from the Georgia Twin Study and data from the National Neighborhood Data Archive and 2000 U.S. Census, I assessed the fit of competing measurement models for family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics. In structural models, I regressed a general externalizing factor (comprising DSM-IV symptoms of ADHD, ODD, and CD) on the latent factors of family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics. Family sociodemographic characteristics were associated with externalizing psychopathology ( $R^2 = .01$ ,  $\beta = -.079$ ,  $SE = .038$ ,  $p = .040$ ), while neighborhood sociodemographic characteristics ( $R^2 = .00$ ,  $\beta = -.016$ ,  $SE = .062$ ,  $p = .800$ ) and neighborhood environment ( $R^2 = .00$ ,  $\beta = .021$ ,  $SE = .061$ ,  $p = .734$ ) were not. Family sociodemographic characteristics were associated with neighborhood sociodemographic characteristics ( $R^2 = .13$ ,  $\beta = -.354$ ,  $SE = .068$ ,  $p < 0.001$ ) and neighborhood environment ( $R^2 = .04$ ,  $\beta = -.186$ ,  $SE = .081$ ,  $p = .022$ ). Results align with prior work indicating family sociodemographic characteristics are associated with externalizing psychopathology. However, when accounting for family sociodemographic characteristics, these results do not support direct associations between neighborhood characteristics and broad externalizing psychopathology.

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# Assessing Structural Models of Neighborhood and Family Sociodemographic Characteristics and Relations with Externalizing Psychopathology

## Introduction

Externalizing psychopathology in youth most typically describes the diagnoses of attention-deficit/hyperactivity disorder (ADHD), oppositional defiant disorder (ODD), and conduct disorder (CD). Broadly characterized by symptoms of disinhibition, antagonism and antisocial behavior (Krueger & Tackett, 2015), externalizing psychopathology is highly prevalent across the lifespan (Kessler et al., 2005) and throughout world, especially in the US where the lifetime prevalence for any externalizing disorder has been estimated at 25% (Kessler et al., 2009). Externalizing psychopathology also incurs high human and financial costs to individuals and society (Barkley, 2020; Christenson et al., 2016; Erskine et al., 2014, 2016; Foster et al., 2005; Rivenbark et al., 2018). An accurate understanding of the etiology of externalizing psychopathology is necessary to relieve the immense burden of these disorders. One common finding in the literature is that aspects of externalizing psychopathology are associated with characteristics of the environment, and specifically family and neighborhood sociodemographic characteristics (Chang et al., 2016; Derzon, 2010; Fowler et al., 2009; Jennings et al., 2018). While studies in this area have contributed greatly to our current etiological understanding of externalizing psychopathology, there are substantive methodological concerns with this literature, which potentially limit our understanding of how and why externalizing psychopathology develops. If not addressed, these methodological limitations may not only inhibit our etiological understanding of these disorders, but also undermine intervention efficacy and our ability to relieve the immense human and financial costs of these disorders.



Much of the prior etiological research on externalizing psychopathology implements a polythetic categorical conceptualization of externalizing psychopathology. This approach posits mental disorders as a set of categorically distinct disorders (either present or not present) if one surpasses a threshold of required symptoms. Comprised of the DSM-V disorders ADHD, ODD, CD and even Intermittent Explosive Disorder (IED) and Disruptive Mood Dysregulation Disorder in childhood, along with substance use disorders (SUD) in adulthood, this polythetic categorical approach of the DSM-V (American Psychiatric Association, 2013) stands in marked contrast to contemporary empirically-supported dimensional models that conceptualize externalizing psychopathology as a spectrum with significant covariation among constituent symptoms (Krueger & Tackett, 2015). Despite some agreement between the externalizing spectrum as instantiated in the Child Behavior Checklist (CBCL) and categorical DSM disorders (Tackett et al., 2003), there are substantive limitations of the DSM approach, specifically issues of within-diagnosis heterogeneity, and cross-diagnosis comorbidity. Etiological studies operationalizing externalizing psychopathology as DSM disorders or constituent symptoms tend to not analytically account for the well-established covariation between these disorders. For example, it has been shown that CD highly cooccurs with ODD (Maughan et al., 2004) and ADHD highly cooccurs with CD and ODD (Biederman et al., 1991; Ollendick et al., 2008). By not specifying the covariance of these disorders, their common etiological basis necessarily cannot be investigated. Likewise, the unique variance and etiological basis of individual disorders cannot be determined. Such imprecision may result in an inaccurate understanding of the etiological basis of these disorders either specifically or as a whole.

In fact, most studies that investigate etiological associations with externalizing psychopathology either implicitly or explicitly implement a categorical polythetic approach. By

doing so, these studies do not account for substantial evidence of shared etiological contributions to externalizing disorders. In contrast, the dimensional model of the externalizing spectrum accounts for the well-replicated empirical finding that externalizing disorders exhibit considerable overlap in symptomatology and frequently covary among individuals (Nikolas, 2015). The dimensional model of the externalizing spectrum addresses these findings by modeling a common factor which all externalizing disorders share, and specific factors exclusive to individual disorders. In doing so, both common and unique contributions to externalizing psychopathology can be empirically investigated. Indeed, behavior genetic studies consistently find significant common genetic, common environmental, unique genetic, and unique environmental influences on externalizing disorders (Burt et al., 2001, 2005; Dick et al., 2005; Ehringer et al., 2006; Kendler & Myers, 2014; Knopik et al., 2014; Krueger et al., 2002; Nadder et al., 2002; Rhee & Waldman, 2002; Silberg et al., 1996; Thapar et al., 2001; Tuvblad et al., 2009; Waldman et al., 2001; Young et al., 2000). The findings from these behavior genetic studies clearly demonstrate the need to model the common and unique etiological bases of externalizing psychopathology.

Among environmental factors, meta-analyses and systematic reviews find small to moderate associations between externalizing psychopathology and family characteristics (Derzon, 2010) and neighborhood characteristics (Chang et al., 2016; Fowler et al., 2009; Jennings et al., 2018). In terms of family, the strongest correlates of externalizing psychopathology include family relationship warmth, stress, socioeconomic status, and history of criminality or substance use (Derzon, 2010). In terms of neighborhood, the strongest correlates include exposure to community violence and neighborhood socioeconomic characteristics (Chang et al., 2016; Fowler et al., 2009; Jennings et al., 2018). Notably, multilevel study designs

that simultaneously control for family and neighborhood variables also find significant associations between externalizing psychopathology and variables at both the family and neighborhood level (Beyers et al., 2003; Romero et al., 2015; Santiago et al., 2011). With respect to aggression specifically, Romano and colleagues (2005) estimated that of the variance in aggression explained by individual, family and neighborhood level variables in a multilevel model, 66% of *explained variance* in aggression was accounted for at the individual level, 30% at the family level and 4% at the neighborhood level. On the surface, these studies would seem to indicate strong support for associations between externalizing psychopathology and both family characteristics and neighborhood characteristics, when not controlling for genetic associations.

However, it is worth noting the typical methodological approaches of studies in this area. In general, these typically cross-sectional or longitudinal studies operationalize externalizing psychopathology with single diagnoses like conduct disorder (e.g., Jennings et al., 2018), a single dimensional symptom like aggression or violence (e.g., Antunes & Ahlin, 2014; Molnar et al., 2005), or related outcomes like criminality/delinquency (e.g., Fabio et al., 2011; Fagan & Wright, 2012). In some cases externalizing is operationalized with a composite scale, for example from the CBCL (e.g., Caughy et al., 2008), the Behavior Problem Index (e.g., Delany-Brumsey et al., 2014) or the Child Health Questionnaire (e.g., Drukker et al., 2010). In neighborhood studies externalizing variables are typically associated with neighborhood sociodemographic characteristics assessed at the census tract level (Flouri & Sarmadi, 2016; Leventhal & Brooks-Gunn, 2011; O'Campo et al., 2010), or self-reported perceptions of neighborhood environment (e.g., Briggs et al., 2015; Callahan et al., 2011), or experiences of community violence (e.g., Linares et al., 2001; Weaver et al., 2008). Similarly, studies of family

characteristics investigate a broad range of family sociodemographic, parenting and psychopathology characteristics with externalizing psychopathology (Derzon, 2010).

There are important methodological limitations, specifically regarding construct operationalization, in this body of research that may limit our understanding of how externalizing disorders develop in the context of the family and neighborhood environment. First, most studies in this area only investigate a single symptom dimension of externalizing such as aggression (Chang et al., 2016) or a single disorder such as CD (Jennings et al., 2018). When studies do operationalize externalizing via a scale, it is often a composite that conflates common and unique variance. These approaches to modelling externalizing disorders may misestimate the extent to which family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics influence externalizing psychopathology broadly. With regards to modelling neighborhood variables, most studies also implement problematic operationalizations of neighborhood sociodemographic characteristics. Studies generally measure only single aspects of neighborhood sociodemographic characteristics or operationalize such constructs with very few items. At their most problematic, these constructs are operationalized with single item measures like percentage of households in public housing, or poverty rate (Flouri & Sarmadi, 2016; Kohen et al., 2009; Lee et al., 2014; Leventhal & Brooks-Gunn, 2011). By using single items, such studies fail to account for other neighborhood features that are potentially relevant to externalizing psychopathology. A number of studies of neighborhood have implemented multiple item composite indices (Beyers et al., 2003; Heberle et al., 2014; Karriker-Jaffe et al., 2009; Molnar et al., 2005; O'Campo et al., 2010). This includes simple composite indices that are commonly used in epidemiology and health outcomes research such as the Townsend Deprivation Index (Townsend et al., 1988) which can be easily computed from standard Census

data in the US, UK or Australia. While these indices are a considerable improvement over single item measures, composite indices also have important limitations in their ability to characterize the full scope of variance and covariance among neighborhood variables. Composite indices may not accurately account for common variance among neighborhood features by conflating common and unique features in the overall score and by not optimally weighting the constituent indicators. In both cases, single or multiple item indices may lead to misestimating the association between the neighborhood and externalizing disorders.

Although some of studies have employed an approach similar to Sampson and colleagues (1997) by optimally weighting factor scores from latent factor analyses, such studies often use relatively few variables to characterize neighborhood sociodemographic characteristics (e.g. Browning et al., 2015; Cleveland, 2003; Fabio et al., 2011; Fagan & Wright, 2012; Farrell et al., 2014; Riina et al., 2013). The few variables employed by these studies may limit their utility to measure facets of the environment most relevant to the development of psychopathology broadly and/or externalizing psychopathology specifically. One index that may address this concern is the Area Deprivation Index (ADI; Singh, 2003) which uses 17 US Census variables including all variables used in the TDI and most variables typically used in the approach following Sampson and colleagues (1997). In fact, associations between the ADI and externalizing have been tested in at least one previous study (Brislin et al., 2021). However, it remains unclear, whether this index, developed and validated for use with other outcomes is optimal for use with mental/behavioral health outcomes. To date there remains no study that has compared the performance of multiple extant deprivation indices and latent variable approaches to family and neighborhood sociodemographic environmental indices to explain variance in mental/behavioral health outcomes, including externalizing psychopathology. Consequently, it remains unclear

which family sociodemographic, neighborhood sociodemographic, and neighborhood environmental indices or variables are most relevant to externalizing psychopathology.

The limitations of extant studies in operationalizing externalizing psychopathology and relevant features of the neighborhood environment must be addressed in order to understand the nature and magnitude of associations between externalizing psychopathology and neighborhood features. First, a study that implements a more accurate model of externalizing psychopathology will provide more accurate estimates of neighborhood associations with more reliable and valid facets of externalizing psychopathology. Such methodological improvement can only benefit our understanding of how neighborhood characteristics relate to this significant and burdensome facet of psychopathology. Second, it is necessary to understand the limitations of extant deprivations indices with respect to psychopathology research. Without a comparative understanding of how well indices and constituent variables characterize features of the neighborhood environment relevant to externalizing psychopathology, it is not possible to assess the accuracy or validity of current quantitative estimates of the association between neighborhood and externalizing. If current measures poorly characterize the neighborhood environment, associations are likely to be misestimated. Implementing an approach such as latent variable modelling across a broader range of variables may address this problem by operationalizing more reliable constructs of neighborhood sociodemographic characteristics that are relevant to externalizing psychopathology. Additionally, expanding the field of variables beyond the use of census-based demographic variables may help to identify a larger set of neighborhood variables relevant to externalizing psychopathology.

### ***The Current Study***

The aim of the current study is to address the aforementioned limitations of prior studies to provide an accurate estimate of the association between externalizing psychopathology and family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics. In a sample of 2197 twins and their siblings, I used a latent variable modelling approach to more accurately operationalize these constructs of interest.

First, to address the limitations of how prior studies have operationalized these constructs, I aimed to determine the best-fitting measurement models for each construct. To do this, I implemented a latent variable modelling approach, and where necessary, used exploratory approaches, subsequently adjudicating between alternative models to determine the best fitting measurement model for each construct. Second, I aimed to evaluate the amount of variance in externalizing psychopathology explained by family sociodemographic, neighborhood sociodemographic, and neighborhood environment latent variables from the best-fitting measurement models. These measurement models were in turn compared to an unconstrained multiple regression model comprising all variables, and, in the case of neighborhood sociodemographic characteristics, two common composite indices of neighborhood deprivation. I hypothesized that the latent variable approach would explain more variance in externalizing psychopathology than other summed indices. Third, I investigated the structural relationships between these constructs by regressing the externalizing latent factor on the latent factors for neighborhood sociodemographic characteristics, family sociodemographic characteristics and neighborhood environment. I hypothesized that decrements in family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics would be associated with higher risk for externalizing disorders. Finally, I aimed to test the exploratory hypotheses that there was a curvilinear association between externalizing psychopathology and

family sociodemographic characteristics, neighborhood sociodemographic characteristics, and neighborhood environment. Overall, this study should greatly improve upon the prior investigations of the association between the neighborhood and externalizing disorders by using more rigorous operationalization of these constructs.

## **Method**

### ***Participants***

Participants were twin pairs and siblings of twins, ages 4-17, selected from the Georgia Twin Registry (GTR), a population-based twin study sample recruited from all 5,620 twins born between 1980 and 1991 for whom birth records were available. The sample was 49% male, 82% Caucasian, 11% African American, 1% Hispanic and 6% other/mixed ancestry. 80% of the sample were twins, and 20% were nontwin siblings. 49% of participants in the sample had a father employed in a white collar or professional/managerial occupation, and 49% of participants in the sample had a mother employed in a white collar or professional/managerial occupation. Family annual income of the sample was as follows: 5% of the sample was below \$20,000, 38% was between \$20,000 and \$50,000, 40% was between \$50,000 and \$90,000, and 18% was above \$90,000. For this study there were complete assessment data and United States postal addresses for 2197 participants out of the 2624 participants originally recruited for the study.

### ***Procedure***

In 1992-1993, parents of 5,620 twins born in Georgia between 1980 and 1991 were mailed a request to join the GTR, by completing and returning a form documenting family demographic information and survey items to determine their twin's zygosity. Of the families contacted, 1,567 agreed to participate in the study. In 1996-1997 parents of twins were mailed a battery of parent report surveys assessing psychopathology symptomatology. Parents were



encouraged to complete the surveys with a monetary compensation of \$10, and reminded via postcards if they had not responded. More information on recruitment methods is provided in (Ficks et al., 2013).

## ***Measures***

### ***Family Sociodemographic Characteristics***

Information regarding family sociodemographic characteristics was collected at the time of study enrollment using a family information form developed for this study. The family information form requests that caregivers provide information regarding family race/ethnicity, family income, parent highest obtained education level, parent occupation and mother's age at date of twins' birth. Family income was categorized into 12 ordinal income brackets. Mother and father education level was categorized in 14 ordinal income brackets. The occupations of the child's mother and father were assigned to a major occupation group according to the Standard Occupational Classification (SOC) coding scheme (Emmel & Cosca, 2010) and categorized as either white collar, non-white collar, or not working where appropriate.

### ***Externalizing Symptomatology***

Participants' primary caregiver completed the Emory Diagnostic Rating Scale (EDRS), which assesses DSM-IV psychiatric symptomatology. Using a Likert scale, caregivers rate their child on a range of behaviors and attributes with 0 indicating "not at all" and 4 indicating "very well". Scores were averaged across each symptom dimension to obtain a symptom scale score. The current study utilized the Inattention, Hyperactivity, Impulsivity, Negative Affect, Deviant Behavior, Aggression, and Rule-Breaking subscales of the EDRS as indicators of externalizing psychopathology. In a prior study of this sample, the EDRS has displayed good to excellent

internal consistency reliability across externalizing disorders;  $\alpha = .91$  for ODD,  $\alpha = .95$  for Inattention, and  $\alpha = .89$  for Hyperactivity-Impulsivity,  $\alpha = .82$  for CD (Ficks et al., 2013).

### ***Neighborhood Sociodemographic Census Variables***

I obtained data from the 2000 US Census at the census tract level to characterize the neighborhood sociodemographic characteristics of study participants. US Census tract data was indexed to participants according to the census tract containing their address at the time of enrollment in the study. For participants who provided P.O. Box and Rural Route addresses at the time of enrollment, a centroid point within the town/city of the participant's listed address was used to identify the census tract. Neighborhood level census tract data in this study includes constituent variables of two neighborhood deprivation indices. Specifically, I used variables from the Townsend Deprivation Index (TDI; Townsend et al., 1988) and the Area Deprivation Index (ADI; Singh, 2003), which also contains the variables of the TDI. The TDI has been extensively used over the past several decades as a measure of resource deprivation and neighborhood sociodemographic characteristics; at the time of this writing the original publication has been cited over 2700 times according to Google Scholar. The TDI is comprised of four variables characterizing a given census tract: the log-transformed unemployment rate, rate of renter households, the log-transformed rate of household overcrowding, and rate of households with access to a motor vehicle. These variables are then standardized as Z scores and summed to form a composite score (Townsend et al., 1988). The Area Deprivation Index was created and has seen extensive use more recently and is comprised of the following variables: rate of adults with under 9 years of education, rate adults with 12 or more years of education, rate of adults with white collar employment, median family income, poverty rate, unemployment rate, rate of households below 150% of the poverty level, income disparity, median home value,

median monthly mortgage, median gross rent, rate of owner occupied units, rate of housing units without plumbing, rate of single-parent households, rate of households with no access to a motor vehicle, rate of households with no phone, rate of household overcrowding. These variables were standardized as Z scores and weighted using factor score coefficients from Singh (2003) to create the ADI composite index.

### ***Neighborhood Environment***

The neighborhood environment was characterized using the 2003 release of the National Neighborhood Data Archive (NaNDA; Finaly et al., 2020). Variables used in this analysis were the per 1000 person densities of bars, dollar stores, liquor stores, tobacco stores, convenience stores, grocery stores, social services, religious organizations, and social/cultural organizations.

### **Analysis**

All latent variable modelling was conducted in Mplus version 8 (Muthén & Muthén, 2017). All modelling implemented Robust Maximum Likelihood estimation. I used the comparative fit index (CFI) the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) to assess model fit. In line with current best practices, values of CFI and TLI over .9, and values of RMSEA below .08 were considered to be good fit (Hu & Bentler, 1999).

Additionally, Bayesian Information Criteria (BIC) was used to compare model fit between non-nested models while accounting for parsimony. Lastly,  $R^2$  values were used to assess differences in the amount of variance explained in the externalizing latent variable featured in structural models.

The analyses consisted of two parts. First, I used confirmatory factor analysis (CFA) and exploratory structural equation modelling (ESEM) to estimate the best-fitting measurement models of the three family and neighborhood sociodemographic latent variables of interest in this

study: family sociodemographic characteristics, neighborhood sociodemographic characteristics, and neighborhood environment characteristics. Additionally, I modelled externalizing, according to forthcoming work by Waldman & Poore (in preparation). Second, I fit a series of models that regressed the externalizing latent factor on the latent variables from the best-fitting measurement models of the family sociodemographic, neighborhood sociodemographic, and neighborhood environment latent variables. This allowed me to estimate the association between the broad externalizing latent factor and the family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics in an optimal way without the biasing effects of measurement error.

### *Measurement Models*

As an aim of this study was to determine the best-fitting factor structure of family sociodemographic, neighborhood sociodemographic, and neighborhood environment variables, I used CFA and ESEM approaches to determine the best-fitting models to characterize these variables. Below I explain in detail the modelling approach I used for each construct.

**Neighborhood Sociodemographic Characteristics.** I used the 17 census variables comprising the ADI, four variables of which also comprise the TDI to test and adjudicate between neighborhood sociodemographic measurement models. I first used all 17 variables to test a range of latent variable model types in models N1-N6. Then, given cases of high multicollinearity between these indicators, which resulted in negative residual variance, or standardized coefficients greater than 1, I also ran versions of models N1-6 that excluded highly multicollinear variables (N1'-N6'). These highly multicollinear variables that were excluded from the amended models N1'-N6' included proportion of adults with more than high school

education, average family income, proportion of households below 150% of the federal poverty line, and monthly mortgage payment

**CFA Models** As the original validation study of the ADI composite index found that a one factor solution best modeled these 17 neighborhood sociodemographic variables (Singh, 2003), I first modeled a one factor model (N1) in which all 17 variables served as indicators of a single factor. As a subsequent study of the ADI has noted four conceptual groupings of these 17 variables (Maroko et al., 2016), I next tested a four correlated factors model (N2) according to these four variable categories (education, income/employment, housing, household characteristics). Next, given conceptual similarity of the variables in the education and income/employment factors, I collapsed these two factors into a single factor to test a three correlated factors model (N3). As previously, noted I also test models (N1'-N3') without highly multicollinear variables. This CFA approach did not yield a neighborhood sociodemographic characteristics measurement model with an acceptable fit.

**ESEM Models** Given that CFA models are often overly restrictive and result in poor model fit, I next used an ESEM approach to identify a neighborhood sociodemographic measurement model with a better fit. The ESEM approach relaxes the more stringent specifications of the CFA model by allowing indicators to load on multiple factors, while still allowing one to test a priori structural relations between latent factors (Marsh et al., 2014). Consequently, I fit 2-4 factor ESEM models (N4-N6). In these models each indicator was allowed to load on all latent factors specified in the model. As previously noted, I also test models (N4'-N6') without highly multicollinear variables. Finally, using the best fitting ESEM model, I implemented an ESEM within CFA approach (EWC) to fit a higher-order model (N7') which featured a single superordinate latent factor for neighborhood sociodemographic characteristics on which the four

specific ESEM factors from model N6' loaded. The EWC approach fixes parameter estimates to the start values obtained from an ESEM model to allow for identification of the EWC model (Morin & Asparouhov, 2018). The EWC approach was required to fit this higher-order model (N7').

***Family Sociodemographic Characteristics.*** Next, I used the family income, mother education, father education, mother occupation, and father occupation variables to characterize the family sociodemographic measurement model. As there were only five indicators available to characterize the family sociodemographic characteristics model, this limited the number of latent factors that could be reasonably specified. Consequently, I fit a single factor model (F1). To improve upon the fit of this model, I also fit a general factor model excluding the variable mother's occupation (F1'), which had a relatively low factor loading and did not characterize the latent factor well relative to other indicators and detracted from model fit.

***Neighborhood Environment.*** Next, for the neighborhood environment measurement model, given that there are no prior investigations of the factor structure of these variables, I used an exploratory approach to identify an optimal measurement model. Using an ESEM approach, I fit 1-3 factor ESEM models (E1-E3). In these ESEM models, each indicator was allowed to load on each latent factor. Finally, using the best fitting ESEM model, I implemented an EWC approach to fit a three factor higher-order factor model (E4) with a single superordinate latent factor for neighborhood environment on which the three specific ESEM factors from model E3 loaded. The EWC approach was required to fit this higher-order model (E4). To identify model E4 following an EWC approach (Morin & Asparouhov, 2018), I fixed parameter estimates to the start values obtained from the best-fitting ESEM.

*Externalizing Psychopathology.* Finally, using CFA, I fit an externalizing measurement model (Z) according to prior work done by Waldman & Poore (in preparation). In this model all indicators loaded on a single factor. This model features correlated residuals between hyperactivity, impulsivity, and inattention, between negative affect and deviant behavior, and between aggression and rule breaking.

### *Structural Models*

To assess the structural relations between externalizing psychopathology and family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics, I fit a series of structural models. In these structural models, I modeled the relationship between the externalizing latent factor and competing measurement models of 1) neighborhood sociodemographic characteristics 2) family sociodemographic characteristics 3) neighborhood environment, and finally 4) all constructs together. For each construct, I first regressed the externalizing latent factor on all variables comprising a given construct in an unconstrained multiple regression model (e.g. externalizing was regressed on the 17 variables used to model the neighborhood sociodemographic measurement models). Next, I regressed the externalizing latent factor on the measurement models of that construct (e.g. the best-fitting neighborhood sociodemographic characteristics measurement model). The  $R^2$  of each unconstrained multiple regression model was compared against the  $R^2$  of the latent variable measurement models for each construct. In the case of neighborhood sociodemographic characteristics these measurement models also included established composite deprivation indices (the ADI and TDI). By comparing the  $R^2$  indices of each unconstrained multiple regression model with each latent variable measurement model and composite index, this

allowed me to assess how well each measurement model explained the variance of the externalizing latent factor.

***Neighborhood Sociodemographic Structural Models.*** To assess the variance of externalizing explained by the neighborhood sociodemographic variables, I fit a model regressing the externalizing latent factor on all 17 neighborhood sociodemographic variables (SN1). In model SN1', I also regressed the externalizing latent factor on the neighborhood sociodemographic variables excluding the highly multicollinear variables dropped from previous measurement models. In model SN2 the externalizing latent factor was regressed on the calculated TDI composite, and in SN3 the externalizing latent factor was regressed on the calculated ADI composite. Model SN4 regressed the externalizing latent factor on the best-fitting latent factor measurement model of neighborhood characteristics (N7').

***Family Sociodemographic Structural Models.*** To assess the variance of externalizing explained by the family sociodemographic variables, in model SF1, I regressed the externalizing latent factor on all family sociodemographic variables in an unconstrained multiple regression model. Model SF1' was the same as SF1, but excluded the variable with the lowest factor loading in Model SF1. Model SF2 regressed the externalizing latent factor on the general factor of the family sociodemographic variables. Model SF2' was the same a SF2, but excluded the variable with the lowest factor loading.

***Neighborhood Environment Models.*** To assess the variance of externalizing explained by all neighborhood environment variables, in model SE1, I regressed the latent externalizing factor on all neighborhood environment variables in an unconstrained multiple regression model. In model SE2 I regressed the latent externalizing factor on the neighborhood environment higher-order latent factor from measurement model E4.



***Final Structural Models.*** To assess the variance of externalizing explained by all family sociodemographic, neighborhood sociodemographic and neighborhood environment variables, in model S1, I regressed the latent externalizing factor on all variables in an unconstrained multiple regression model. Model S1' was the same as S1, but excluded the variables dropped from prior neighborhood sociodemographic and family sociodemographic models. Finally, to investigate the structural relationships between the externalizing latent factor and neighborhood sociodemographic, family sociodemographic and neighborhood environment characteristics, model Z featured the externalizing factor regressed on the common factor of family sociodemographic characteristics, the higher-order latent factor of neighborhood sociodemographic characteristics, and the higher-order latent factor of neighborhood environment. These three latent factors on which externalizing was regressed, were allowed to correlate in the model. This allowed me to test the structural relations between these variables.

***Exploratory Structural Models.*** Finally, I tested the exploratory hypotheses that there was a quadratic curvilinear association between externalizing and 1) family sociodemographic characteristics, 2) neighborhood sociodemographic characteristics, and 3) neighborhood environment. To test for the quadratic association between externalizing and family sociodemographic characteristics, I modelled a squared family sociodemographic general latent factor on which externalizing was regressed. To test for the quadratic association between externalizing and neighborhood sociodemographic characteristics, I modelled a squared neighborhood sociodemographic higher-order latent factor on which externalizing was regressed. To test for the quadratic association between externalizing and neighborhood environment, I modelled a squared neighborhood environment latent factor on which externalizing was regressed.

## Results

### *Measurement Models*

Measurement model fit indices for neighborhood sociodemographic characteristics, family sociodemographic characteristics, neighborhood environment characteristics, and externalizing psychopathology are presented in Table 1.  $\chi^2$ , CFI, TLI, BIC and RMSEA fit indices were used to evaluate model fit for each measurement model.

**Neighborhood Sociodemographic Characteristics.** Generally, CFA models of neighborhood sociodemographic characteristics displayed poor fit. Model fit was poorest for the CFA models that used all ADI variables as indicators. This included the general factor model (N1; CFI = .54, TLI = .47, RMSEA = .10, BIC = 128264), four correlated factors model (N2; CFI = .69, TLI = .63, RMSEA = .08, BIC = 120864) and three correlated factors model (N3; CFI = .43, TLI = .33, RMSEA = .11, BIC = 125121). This poor fit was likely attributable in part to high multicollinearity of several constituent variables, as evidenced by several correlations between variables in excess of .9. Consequently, models N2 and N3 featured negative residual variance and correlations between latent factors or standardized factor loadings in excess of 1. Model fit was improved by removing the following highly multicollinear variables: proportion of adults with more than high school education, average family income, proportion of households below 150% of the federal poverty line, and monthly mortgage payment. Subsequently, the models N1' (CFI = .69, TLI = .62, RMSEA = .07, BIC = 117610), N2' (CFI = .73, TLI = .64, RMSEA = .07, BIC = 104847.56) and N3' (CFI = .70, TLI = .62, RMSEA = .07, BIC = 105104) had better but still suboptimal fit.

I next used an ESEM approach to relax the more stringent specifications of CFA to identify a model with more optimal fit. I fit ESEM models ranging from 2-4 factors. All ESEM

2-4 factors models displayed relatively better fit than CFA models. The two factor ESEM model (N4; CFI = .78, TLI = .71, RMSEA = .07, BIC = 117610) and three factor ESEM model (N5; CFI = .90, TLI = .84, RMSEA = .05, BIC = 113407) displayed better but still suboptimal fit. Both models N4 and N5 also featured standardized factor loadings greater than 1, and model N5 featured negative residual variance, likely due to high multicollinearity among indicator variables. The ESEM 4 factors model (N6; CFI = .94, TLI = .89, RMSEA = .04, BIC = 111900) displayed adequate fit, however, it still featured negative residual variances and standardized factor loadings greater than 1. Subsequently, ESEM 2-4 factors models were fit without the same highly multicollinear variables that were dropped in the previous models. The amended two factors ESEM model (N4'; CFI = .82, TLI = .74, RMSEA = .06, BIC = 103424), amended three factors ESEM model (N5'; CFI=.89, TLI=.80, RMSEA=.05, BIC=102217), and amended four factors ESEM model (N6'; CFI=.95, TLI=.88, RMSEA=.04, BIC=101527) fit marginally better than their equivalent unamended models, and none featured issues with negative residual variance or standardized factor loadings greater than 1. The amended four factor ESEM model displayed good-to-excellent fit and was subsequently used to fit a higher order factor model via an ESEM within CFA approach (EWC). The resulting model N7' (CFI=.95, TLI=.89, RMSEA=.04, BIC=101547) displayed equivalent fit, while also featuring a single higher order neighborhood sociodemographic characteristics factor that could be used to predict externalizing in subsequent structural models. The standardized factor loadings and factor reliability indices for model N7' are presented in Table 2.

**Family Sociodemographic Characteristics Model.** A general factor model featuring all family sociodemographic variables (F1; CFI = .86, TLI = .72, RMSEA = .08, BIC = 28065) had suboptimal fit. The indicator “mother’s white collar occupation status” had a low loading ( $\beta =$

.29, SE = .06) on this factor relative to other indicators and was dropped in the subsequent measurement model to improve model fit. This amended general factor model had good-to-excellent fit (F1'; CFI = .96, TLI = .89, RMSEA = .06, BIC = 25211). This measurement model was used in subsequent structural modelling. The standardized factor loadings and factor reliability indices for model F1' are presented in Table 3.

***Neighborhood Environment Measurement Model.*** Given that there are no prior investigations of the factor structure of these neighborhood environment variables, I used an ESEM approach to identify an optimal measurement model. I tested 1-3 factor ESEM models as measurement models for the neighborhood environment. The ESEM 1 factor model (E1; CFI = .86, TLI = .81, RMSEA = .07, BIC = 82615) displayed suboptimal fit. The ESEM 2 factor model (E2; CFI = .98, TLI = .95, RMSEA = .03, BIC = 82021) displayed excellent fit, while the ESEM 3 factor model (E3; CFI = .99, TLI = .98, RMSEA = .02, BIC = 81861) displayed the best fit of the ESEM models and was subsequently used to fit a higher order factor model via an ESEM within CFA approach (EWC). The resulting model E4 (CFI = 1.00, TLI = .99, RMSEA = .01, BIC = 81854) displayed better fit while featuring a single higher order neighborhood environment factor that could be used to predict externalizing in subsequent structural models. The standardized factor loadings and factor reliability indices for model E4 are presented in Table 4.

***Externalizing Measurement Model.*** The general factor model of externalizing psychopathology (Z; CFI = .99, TLI = .97, RMSEA = .05, AIC = 54570) displayed excellent fit. The factor loadings and factor reliability indices for model Z are presented in Table 5.

## **Structural Models**

Structural models were used to assess associations between the externalizing latent factor and the family sociodemographic, neighborhood sociodemographic, and neighborhood environment characteristics. The model fit statistics and the  $R^2$  for externalizing in each of these models are presented in Table 6.

***Neighborhood Sociodemographic Characteristics.*** The model in which the externalizing latent factor was regressed on all ADI variables in an unconstrained multiple regression model (SN1) did not explain significant variance ( $R^2 = .012$ ,  $p = .158$ ) in the externalizing latent factor. The subsequent model SN1' in which the highly multicollinear ADI variables were dropped also did not explain significant variance ( $R^2 = .010$ ,  $p = .215$ ) in the general externalizing latent factor. In model SN2, the TDI composite also did not explain significant variance ( $R^2 = .001$ ,  $p = .615$ ) in the externalizing latent factor, nor did the ADI composite ( $R^2 = .002$ ,  $p = .440$ ) in model SN3. Finally, a model in which the externalizing latent factor was regressed on the higher order neighborhood sociodemographic latent factor (SN4; CFI = .95, TLI = .93, RMSEA = .03) also did not explain significant variance in the externalizing latent factor ( $R^2 = .002$ ,  $p = .546$ ).

***Family Sociodemographic Characteristics.*** The model in which the externalizing factor was regressed on all family sociodemographic variables in an unconstrained multiple regression model (SF1) explained significant variance ( $R^2 = .020$ ,  $p = .017$ ) in the general externalizing factor. An model similar to SF1 in which the “mother’s occupation status” variable was dropped (SF1') also explained significant variance ( $R^2 = .017$ ,  $p = .032$ ) in the general externalizing latent factor. In model SF2' (CFI = .97, TLI = .96, RMSEA = .04), the general family sociodemographic latent factor did not explain significant variance in the externalizing latent factor ( $R^2 = .009$ ,  $p = .186$ ).

**Neighborhood Environment.** The model in which the externalizing factor was regressed on all neighborhood environment variables in an unconstrained multiple regression model (SE1) explained significant variance ( $R^2 = .014$ ,  $p = .032$ ) in the general externalizing factor. However, in model SE2 (CFI = .99, TLI = .99, RMSEA = .02), the higher order neighborhood environment factor did not explain significant variance in the externalizing latent factor ( $R^2 = .000$ ,  $p = .772$ )

**All variables.** Finally, the externalizing factor was regressed on all variables used in prior measurement modelling in a multiple regression model (SA1). These variables collectively explained significant variance ( $R^2 = .041$ ,  $p = .001$ ) in the externalizing latent factor. Another model in which the externalizing latent factor was regressed on all variables sans the highly multicollinear variables dropped in previous measurement models (SA1') also explained significant variance ( $R^2 = .036$ ,  $p = .001$ ) in the general externalizing latent factor. In the full structural model (S1; CFI = .87, TLI = .85, RMSEA = .04), the family sociodemographic latent factor, the neighborhood sociodemographic higher order latent factor, and the higher order neighborhood environment latent factor together did not explain significant variance in the externalizing latent factor ( $R^2 = .009$ ,  $p = .182$ ). The structural relations between the latent factors in the final model are presented in Figure 1. The standardized factor loadings and factor reliability indices for this model are presented Table 7. In the final model, the family sociodemographic latent factor was significantly associated with the general externalizing latent factor ( $R^2 = .009$ ,  $\beta = -0.08$ ,  $SE = .04$ ,  $p = .040$ ), such that higher family SES was associated with lower youth externalizing. Neither the neighborhood sociodemographic factor ( $R^2 = .000$ ,  $\beta = -0.01$ ,  $SE = .06$ ,  $p = .800$ ) nor neighborhood environment factor ( $R^2 = .000$ ,  $\beta = 0.01$ ,  $SE = .06$ ,  $p = .734$ ) were significantly associated with the externalizing factor. However, the neighborhood sociodemographic and neighborhood environment factors were significantly correlated with each

other ( $\beta = 0.75$ ,  $SE = .05$ ,  $p < .001$ ) such that higher neighborhood SES was associated with a better neighborhood environment factor. Family SES was also associated with neighborhood SES ( $\beta = -.35$ ,  $SE = .07$ ,  $p < .001$ ; note that the neighborhood sociodemographic factor is characterized by indicators of low sociodemographic status) such that higher family SES was associated with higher neighborhood SES. Family SES was also associated with the neighborhood environment factor ( $\beta = -.91$ ,  $SE = .08$ ,  $p = .022$ ; note that the neighborhood environment factor is characterized by indicators of environmental risk) such that higher family SES was also associated with a better neighborhood environment.

### **Exploratory Structural Models**

Finally, I tested the exploratory hypotheses that there was a quadratic curvilinear association between 1) externalizing and family sociodemographic characteristics, 2) externalizing and neighborhood sociodemographic characteristics, and 3) externalizing and neighborhood environment. These results indicated no support for a quadratic curvilinear association between externalizing and neighborhood sociodemographic characteristics ( $\beta = -.03$ ,  $SE = .02$ ,  $p = .130$ ). There was no support for a quadratic curvilinear association between externalizing and neighborhood environment ( $\beta = -.011$ ,  $SE = .01$ ,  $p = .073$ ). Finally, there was no support for a curvilinear association between externalizing and family sociodemographic characteristics ( $\beta = -.04$ ,  $SE = .05$ ,  $p = .454$ ).

### **Discussion**

In this study I assessed the operationalizations of family sociodemographic characteristics, neighborhood sociodemographic characteristics, and neighborhood environment and their relations with externalizing psychopathology. Previously, studies of the association between externalizing psychopathology and family and neighborhood characteristics have

employed suboptimal operationalizations of these variables (Chang et al., 2016; Derzon, 2010; Jennings et al., 2018), potentially undermining accurate estimates of the associations between them. These previous studies have typically used single-item, or very limited composite indices that fail to account for shared variance between multiple indicator variables. To address these limitations, I used a latent variable modelling approach, first adjudicating among alternative measurement models of family sociodemographic, neighborhood sociodemographic, and neighborhood environment constructs, and then evaluating the structural relations between them and externalizing.

Findings from latent variable measurement models indicated that the best-fitting measurement model of each construct had good to excellent fit. However, results from structural models indicated that the neighborhood sociodemographic latent variable did not explain any more variance in broad externalizing psychopathology than composite indices. Indeed, neither the neighborhood sociodemographic latent variable, nor neighborhood sociodemographic composite indices, explained significant variance in broad externalizing psychopathology in this study. Results from the final structural model indicated that only family sociodemographic characteristics were associated with externalizing psychopathology and that this association was small ( $R^2 = .009$ ). In this final structural model, neighborhood sociodemographic characteristics and neighborhood environment were not associated with externalizing psychopathology, but did have a small to moderate association with family sociodemographic characteristics and a large association with each other. Below I discuss the implications of these findings in detail.

For the first aim of this study, I used both CFA and ESEM approaches to determine the best-fitting measurement model for family sociodemographic characteristics, neighborhood sociodemographic characteristics, neighborhood environment, and externalizing



psychopathology. All best-fitting measurement models for these constructs had good to excellent fit. With respect to family sociodemographic characteristics, a single factor model fit best, and with respect to neighborhood environment a higher-order 3 factor ESEM model fit best. Notably, contrary to prior work by Singh (2003), variables comprising the ADI were not best modeled as loading exclusively on a single factor. Instead, fit indices indicated that a 4 factor higher-order ESEM model fit the data considerably better than a single factor model. Notably, only a limited number of prior studies have used a latent variable modeling approach to operationalize neighborhood sociodemographic characteristics. These studies typically follow the approach of Sampson and colleagues (1997) and only use a limited number of neighborhood sociodemographic variables. The current study provides an important contribution to the literature by determining a more optimal factor structure for a wider range of neighborhood sociodemographic characteristics than is typically used in studies of externalizing psychopathology.

As a second aim of this study, I evaluated the variance of externalizing psychopathology explained by the common factors of the best-fitting latent variable measurement models compared to composite indices and unconstrained multiple regression models. Within an unconstrained multiple regression model, family sociodemographic variables explained significant variance in externalizing psychopathology. Within a separate unconstrained multiple regression model, neighborhood environment variables also explained significant variance in externalizing psychopathology. However, this was not the case for neighborhood sociodemographic variables. Notably, the common factors of family sociodemographic, neighborhood sociodemographic and neighborhood environment constructs did not explain significant variance in externalizing when externalizing was regressed on each latent factor

separately. Further, composite indices of neighborhood sociodemographic characteristics (the TDI and ADI) also did not explain significant variance in externalizing psychopathology. Given many prior reports of small to moderate associations between externalizing psychopathology and neighborhood sociodemographic characteristics (Chang et al., 2016; Jennings et al., 2018), these results are unexpected. Additionally, curvilinear (i.e., quadratic) associations between externalizing psychopathology and the family and neighborhood sociodemographic characteristics were not supported.

As a third aim of this study, I evaluated the associations between family sociodemographic characteristics, neighborhood sociodemographic characteristics, neighborhood environment and externalizing psychopathology simultaneously in a final structural model. Results from this model indicated that only family sociodemographic characteristics were directly associated with broad externalizing psychopathology when controlling for neighborhood sociodemographic characteristics and neighborhood environment. Notably, this association between externalizing psychopathology and family sociodemographic characteristics was small ( $R^2 = .009$ ). Family sociodemographic characteristics also had a small-to-moderate association with neighborhood environment and a moderate association with neighborhood sociodemographic characteristics.

Previous studies have generally found small to moderate associations between externalizing psychopathology and family sociodemographic characteristics (Derzon, 2010) and neighborhood sociodemographic characteristics (Chang et al., 2016; Fowler et al., 2009; Jennings et al., 2018). Notably, in line with these prior studies, results from the current study do support a small association between externalizing psychopathology and family sociodemographic characteristics. In contrast with prior studies, the current study does not

support an association between externalizing psychopathology and neighborhood sociodemographic characteristics.

Notably, this is the first study to adjudicate between multiple operationalizations of neighborhood sociodemographic characteristics and to assess the performance of these operationalizations in explaining the variance of broad externalizing psychopathology. It is also one of the few studies to have found a null association between externalizing psychopathology and neighborhood sociodemographic characteristics (Brislin et al., 2021; Pajer et al., 2008; Riina et al., 2013). Importantly, this null finding should not simply be attributed to how these constructs were operationalized in the structural models of the current study. Indeed, the many alternative operationalizations of neighborhood sociodemographic characteristics tested in this study also did not explain significant variance in externalizing psychopathology. This included operationalizations of neighborhood sociodemographic characteristics similar to those used in previous studies that did find small to moderate associations. Even in the unconstrained multiple regression model, neighborhood sociodemographic variables did not explain significant variance in externalizing psychopathology. In sum, neighborhood sociodemographic characteristics were simply not associated with externalizing in the current study.

Lastly, this study makes an important contribution to the literature by simultaneously modelling the structural relations between family sociodemographic characteristics, neighborhood sociodemographic characteristics, neighborhood environment and externalizing psychopathology. Prior work has not modeled the relations of these constructs simultaneously. Consequently, it has remained unclear whether prior associations found between externalizing psychopathology and family sociodemographic characteristics are present even when controlling for neighborhood sociodemographic characteristics or neighborhood environment, and vice

versa. It is notable that even when controlling for neighborhood sociodemographic characteristics and neighborhood environment, family sociodemographic characteristics were still associated with externalizing psychopathology. Thus, the current study provides more rigorous support for the previously reported small-to-moderate associations between externalizing psychopathology and family sociodemographic characteristics. By the same token, the results of this study also call into question prior reports of the direct association between externalizing psychopathology and neighborhood sociodemographic characteristics.

### ***Limitations and Future Directions***

There are important limitations to the current study that should be addressed in future work. First, it is important to note the limitations of the neighborhood constructs as operationalized in this study. Specifically, one's neighborhood of residence was assessed only at the time of recruitment. Therefore, it is not possible to assess the extent to which individuals moved and were exposed to neighborhoods different from their neighborhood residence at the time of recruitment. It is possible that the neighborhood residence at time of recruitment is not an accurate indicator of exposure to neighborhood risk factors across participants' childhood. Additionally, while generally considered to be the best objective indicator of neighborhood, assessing participants' neighborhood by US Census Tract has inherent limitations, as individuals' experiences of neighborhood may not cleanly align with tract boundaries (Basta et al., 2010). Additionally, the different individuals within the same tract may have substantively different experiences of the neighborhood. Future work should implement more precise specifications of participants' neighborhoods, perhaps including aspects of their subjective reports of their neighborhood environment,

Additionally, this study did not account for genetic associations with these variables. For example, genetic associations may explain variance in both externalizing psychopathology and family sociodemographic or neighborhood sociodemographic characteristics, as well as their relations, thereby resulting in misestimates of the association between externalizing psychopathology and family sociodemographic or neighborhood sociodemographic characteristics. Future work should more rigorously control for the possibility of genetic associations with these variables to further improve the accurate estimates of these associations.

Lastly, there are important limitations to the generalizability of this study. Participants were born from 1980 to 1991. To the extent that cohort effects may have influenced these findings, the results of this study may not generalize well to other generational cohorts. Additionally, most participants were born in and living in Georgia at the time of recruitment. Findings regarding the association between neighborhood sociodemographic and neighborhood environment and externalizing in this specific geographic region may not generalize well to neighborhoods in other geographic regions of the US. Future work should seek to utilize nationally representative samples across many generational cohorts.

### ***Conclusion***

In summary, this study finds that family sociodemographic characteristics are associated with broad externalizing psychopathology while controlling for neighborhood sociodemographic characteristics and neighborhood environment. These results do not support direct associations between broad externalizing psychopathology and neighborhood sociodemographic characteristics or neighborhood environment.

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## Tables

Table 1. Measurement Model Fit Statistics

Model	$\chi^2$ (df)	CFI	TLI	BIC	RMSEA
<b>Neighborhood Sociodemographic Models</b>					
N1. General Factor	2611.44 (119)	.54	.47	128264	.10
N1.' General Factor - Amended	817.34 (65)	.69	.62	105884	.07
N2. 4 Correlated Factors	1780.09 (113)	.69	.63	120864	.08
N2.' 4 Correlated Factors - Amended	713.13 (59)	.73	.64	105104	.07
N3. 3 Correlated Factors	3166 (116)	.43	.33	125121	.11
N3.' 3 Correlated Factors - Amended	789.99 (62)	.70	.62	105704	.07
N4. ESEM 2 Factor	1264.51 (103)	.78	.71	117610	.07
N4.' ESEM 2 Factor - Amended	483.85 (53)	.82	.74	103424	.06
N5. ESEM 3 Factor	629.21 (88)	.90	.84	113407	.05
N5.' ESEM 3 Factor - Amended	295.01 (42)	.89	.80	102217	.05
N6. ESEM 4 Factor	408.68 (74)	.94	.89	111900	.05
N6.' ESEM 4 Factor - Amended	148.05 (32)	.95	.88	101527	.04
<b>*N7'. EWC Higher Order 4 Factor</b>	<b>153.5 (34)</b>	<b>.95</b>	<b>.89</b>	<b>101547</b>	<b>.04</b>
<b>Family Sociodemographic Models</b>					
F1. General Factor	81.91 (5)	.86	.72	28065	.08
<b>*F1.' General Factor - Amended</b>	<b>17.22 (2)</b>	<b>.96</b>	<b>.89</b>	<b>25211</b>	<b>.06</b>
<b>Neighborhood Environment Models</b>					
E1. ESEM 1 Factor	308.74 (27)	.86	.81	82615	.07
E2. ESEM 2 Factor	66.87 (19)	.98	.95	82021	.03
E3. ESEM 3 Factor	27.08 (12)	.99	.98	81861	.02
<b>*E4. EWC HO 3 Factor</b>	<b>17.81 (13)</b>	<b>1.00</b>	<b>.99</b>	<b>81854</b>	<b>.01</b>
<b>Externalizing Measurement Model</b>					
<b>*Z. General Factor</b>	<b>54.02 (9)</b>	<b>.99</b>	<b>.97</b>	<b>54718</b>	<b>.05</b>

*Note.* \* = best-fitting model; ESEM = Exploratory Structural Equation Modelling; Amended Neighborhood Sociodemographic Models drop the following highly multicollinear variables: proportion of adults with more than high school education, average family income, proportion of households below 150% of the federal poverty line, and monthly mortgage payment; The Amended Family Sociodemographic Model drops mother white collar occupation status.

**Table 2. Best Fitting Neighborhood Sociodemographic Measurement Model N7'**

Indicator	Factors				N
	NH1	NH2	NH3	NH4	
Education <9 years	<b>.69 (.03)***</b>	-.01 (.00)***	-.02 (.00)***	<b>.45 (.05)***</b>	
Adults with White Collar Job	-.16 (.04)***	<b>.72 (.04)***</b>	-.02 (.03)	<b>-.28 (.03)***</b>	
Poverty Rate	<b>.69 (.03)***</b>	-.05 (.00)***	<b>.45 (.04)***</b>	-.09 (.01)***	
Unemployment Rate	<b>.33 (.05)***</b>	-.03 (.06)	<b>.42 (.08)***</b>	-.02 (.05)	
Income Disparity	<b>.52 (.03)***</b>	<b>-.27 (.03)***</b>	<b>.29 (.03)***</b>	.00 (.02)	
Median Home Value	.00 (.00)***	<b>.81 (.03)***</b>	.02 (.00)***	-.05 (.01)***	
Median Monthly Rent	<b>-.47 (.05)***</b>	<b>.44 (.04)***</b>	.06 (.03)	.04 (.03)	
Owner Occupied Housing	-.10 (.08)	-.07 (.08)	<b>-.71 (.03)***</b>	-.05 (.06)	
Housing with no Plumbing	<b>.39 (.06)***</b>	-.09 (.05)	-.08 (.05)	.06 (.05)	
Single Parent Households	-.03 (.00)***	<b>-.44 (.04)***</b>	<b>.62 (.04)***</b>	.00 (.00)***	
Households with no Car	<b>.56 (.05)***</b>	.11 (.04)**	<b>.50 (.07)***</b>	.02 (.05)	
Households with no Phone	<b>.81 (.05)***</b>	-.01 (.06)	.04 (.04)	.05 (.05)	
Overcrowded Households	-.08 (.09)	-.09 (.10)	<b>.62 (.07)***</b>	<b>.55 (.09)***</b>	
NH1					<b>.87 (.13)***</b>
NH2					<b>-.69 (.09)***</b>
NH3					<b>.46 (.06)***</b>
NH4					<b>.37 (.11)**</b>
FL Std. Error	.08	.08	.07	.05	.11
FL Std. Dev.	.28	.28	.27	.18	.23
FL Mean	.37	.24	.30	.13	.60
FL Median	.39	.09	.29	.05	.58
H	.84	.78	.76	.45	.81
Mean FL Std. Error	.08				
Mean FL Std. Dev.	.25				
Mean FL Mean	.33				
Mean FL Median	.28				
Mean H	.73				

*Note.* \*\*\* $p < .001$ ; \*\* $p < .01$ ; FL = Factor Loading; Bolded factor loadings represent factor loadings greater than or equal to .25

**Table 3. Best Fitting Family Sociodemographic Model F1'**

<b>Indicator</b>	<b>FAM</b>
Family Income	.60 (.04)***
Mother's Education	.59 (.03)***
Father's Education	.80 (.04)***
Father's White Collar Occupation Status	.47 (.04)***
FL Std. Error	.07
FL Std. Dev.	.14
FL Mean	.62
FL Median	.60
H	.76

*Note.* \*\*\* $p < .001$ ; FL = Factor Loading

**Table 4. Best-Fitting Neighborhood Environment Measurement Model E4**

<b>Indicators</b>	<b>Factors</b>			
	<b>ENV1</b>	<b>ENV2</b>	<b>ENV3</b>	<b>E</b>
Bars	-.01 (.00)***	<b>.57 (.13)***</b>	.18 (.04)***	
Dollar Stores	<b>.63 (.16)***</b>	.02 (.11)	-.21 (.16)	
Liquor Stores	<b>.28 (.14)*</b>	<b>.24 (.11)*</b>	-.11 (.13)	
Tobacco Stores	.04 (.15)	<b>.34 (.13)**</b>	-.23 (.15)	
Convenience Stores	<b>.79 (.04)***</b>	<b>-.27 (.10)**</b>	.01 (.00)**	
Grocery Stores	<b>.54 (.13)***</b>	<b>.26 (.08)**</b>	.00 (.13)	
Social Services	-.01 (.00)***	<b>.63 (.08)***</b>	<b>.45 (.08)***</b>	
Religious Organizations	<b>.47 (.13)***</b>	-.01 (.10)	<b>.45 (.09)***</b>	
Social/Cultural Organizations	.06 (.11)	<b>.37 (.14)**</b>	<b>.52 (.11)***</b>	
ENV1				<b>1.00 (.05)***</b>
ENV2				<b>.46 (.19)*</b>
ENV3				<b>.49 (.29)</b>
FL Std. Error	.10	.07	.06	.18
FL Std. Dev.	.30	.21	.19	.30
FL Mean	.31	.30	.24	.65
FL Median	.28	.27	.21	.49
H	.76	.62	.51	1.00
Mean FL Std. Error	.10			
Mean FL Std. Dev.	.25			
Mean FL Mean	.38			
Mean FL Median	.31			
Mean H	.72			

*Note.* \*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ; FL = Factor Loading; Bolded factor loadings represent factor loadings greater than or equal to .25; The ENV1 factor loading on E was fixed to 1 for identification purposes

**Table 5. Externalizing Measurement Model**

	EXT
Inattention	.61 (.02)***
Hyperactivity	.60 (.03)***
Impulsivity	.61 (.02)***
Negative Affect	.75 (.02)***
Deviant Behavior	.84 (.02)***
Aggression	.68 (.02)***
Rule Breaking	.72 (.02)***
FL Std. Error	0.03
FL Std. Dev.	0.09
FL Mean	0.69
FL Median	0.68
H	0.88

*Note.* All factor loadings significant at  $p < .001$ ; FL = Factor Loading; EXT = Externalizing Latent Factor; (Factor Correlations: Inattention with Hyperactivity  $r = .33$ , Inattention with Impulsivity  $r = .13$ , Hyperactivity with Impulsivity  $r = .48$ , Negative Affect with Deviant Behavior  $r = .51$ , Aggression with Rule Breaking  $r = .17$ )

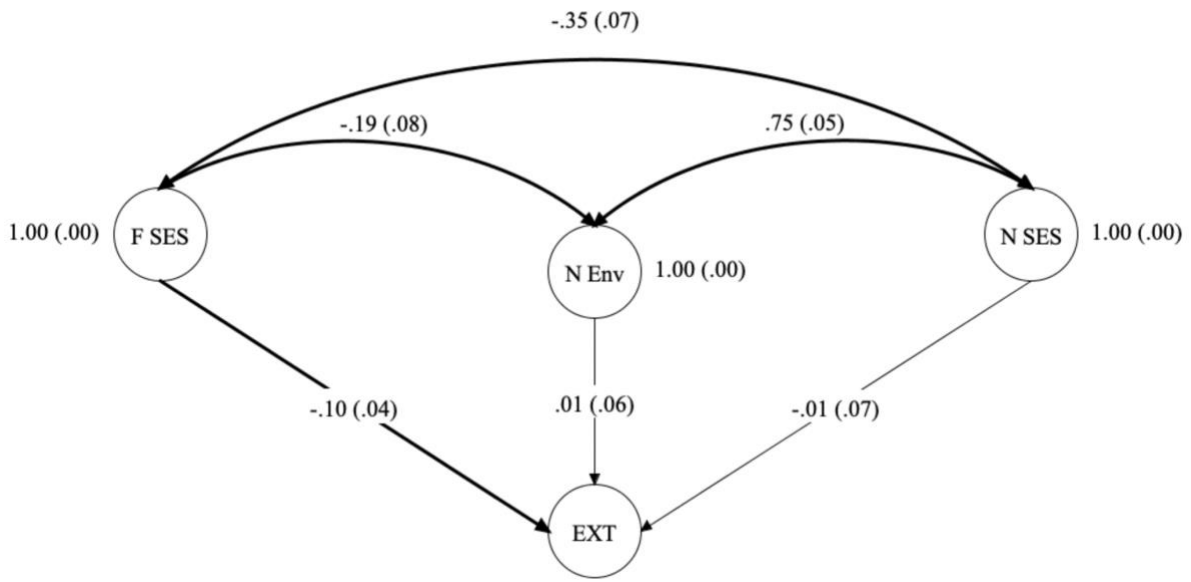
**Table 6. Structural Model Fit Indices**

<b>Model</b>	$\chi^2$ (df)	<b>CFI</b>	<b>TLI</b>	<b>BIC</b>	<b>RMSEA</b>	<b>EXT R<sup>2</sup></b>	<b>R<sup>2</sup> p-value</b>
<b>Neighborhood Sociodemographic Characteristics</b>							
SN1. Multiple Regression – EXT on ADI variables	179 (111)	.99	.99	164734	.02	.01	.158
SN1'. Multiple Regression – EXT on ADI variables	148 (87)	.99	.99	155645	.02	.01	.215
SN2. EXT on TDI composite	68 (15)	.99	.98	54724	.04	.00	.613
SN3. EXT on ADI composite	72 (15)	.99	.98	54723	.04	.00	.722
SN4'. EXT on NH Sociodemographic Factor	446 (133)	.95	.93	156270	.03	.00	.546
<b>Family Sociodemographic Characteristics</b>							
SF1. Multiple Regression – EXT on Family Sociodemographic variables	108 (39)	.99	.98	82602	.03	.02	.017
SF1'. Multiple Regression – EXT on Family Sociodemographic variables	99 (33)	.99	.98	79890	.03	.02	.032
SF2. EXT on Family Sociodemographic Factor	330 (49)	.95	.93	82897	.05	.01	.234
SF2'. EXT on Family Sociodemographic Factor	192 (39)	.97	.96	82897	.04	.01	.186
<b>Neighborhood Environment</b>							
SE1. Multiple Regression – EXT on NH Environment Variables	138 (63)	.99	.98	136622	.02	.01	.032
SE2. EXT on NH Environment Factor	130 (87)	.99	.99	136556	.02	.00	.772
<b>All Variables Model</b>							
SA1. Multiple Regression – EXT on all variables	294 (195)	.98	.98	271870	.02	.04	.001
SA1'. Multiple Regression – EXT on all variables	254 (165)	.99	.98	259845	.02	.04	.001
S1. Full Structural Model	2079 (443)	.87	.85	262398	.04	.01	.182

*Note.* EXT = The externalizing general factor; TDI = Townsend Deprivation Index; ADI = Area Deprivation Index; Models SN1' and SN4' drop the following highly multicollinear variables: proportion of adults with more than high school education, average family income, proportion of households below 150% of the federal poverty line, and monthly mortgage payment, Model SF1' and SF2' drops mother white collar occupation status, while models SA1' and S1 drop all these variables.

### Figures

Figure 1. Final Structural Model



*Note.* EXT = externalizing psychopathology; F SES = family sociodemographic characteristics; N Env = neighborhood environment; N SES = neighborhood sociodemographic characteristics