Explaining Income Disparities in Young Children's Development: The Role of Community Contexts and Family Processes

Abstract

Growing economic disparities and the increased sorting of families into economically segregated communities have heightened the need to clearly delineate pathways through which family income promotes children's development. Combining hypotheses from investment and stress theories, we developed and tested a multi-context and cross-domain conceptual model assessing how community and family contexts mediate links between family income and children's cognitive and behavioral skills at kindergarten entry. We drew data on family income, parenting processes, and child functioning from the Early Childhood Longitudinal Study– Birth Cohort (ECLS-B; $N \approx 10{,}650$), following children from infancy through age 5. We used Geographic Information Systems technology to create and validate community measures using administrative data from the Economic Census, Decennial Census, National Center of Education Statistics, Federal Bureau of Investigations, and Environmental Protection Agency, which were then linked to each child in the ECLS-B. Using structural equation modeling, our analyses revealed three primary lessons. First, lower-income children have limited access to community educational and cultural resources and heightened exposure to community stressors including concentrated disadvantage and violent crime. Second, these community features are associated with parenting processes, such that parent-child interactions tend to be less stimulating and supportive and more punitive in communities with fewer resources and heightened stressors. And third, community and family contexts together mediate connections between family income and children's cognitive and behavioral functioning. Results, albeit showing small effect sizes,

provide a more complex, multi-contextual view than prior research, delineating the role of both resources and stressors at community and family levels in explaining income disparities in young children's developmental success.

Keywords: poverty, income disparities, parenting, stress, resources, school readiness

Income Disparities in Young Children's Development

The U.S. is experiencing a pattern of dramatic growth in income inequality, with affluent families gaining a greater portion of resources and lower- and middle-income families falling further behind (Bradbury & Triest, 2016). Income inequality is becoming more spatially concentrated as well, with rising income segregation across neighborhoods and schools leading to the increasing economic isolation of children and families (Bischoff & Reardon 2014; Owens, Reardon, & Jencks 2016; Owens 2018). Given interlocking systems of economic and racial oppression, the fallout from these shifts is likely to be felt most acutely by people of color. Not only have systemic racism and colonization contributed to the consistent over-representation of White families at the top of the income distribution at the expense of Black, Latinx, and Indigenous communities (Asante Muhammed, Tec & Ramirez, 2019; Collins, Asante-Muhammed, Hoxie & Terry, 2019; U.S. Census Bureau, 2018), but it is within communities of color that income inequality is most extreme (Kochhar & Cilluffo, 2018). In the face of mounting evidence of the intergenerational transmission of advantage and disadvantage (Bradbury & Triest, 2016; Reardon, 2011), these patterns underscore the need to unpack how family income contributes to child development and identify levers through which to disrupt these enduring inequities.

A growing body of research shows causal effects of family income on young children's cognitive and behavioral skills that function above and beyond correlated characteristics of families such as parental education, marital status, immigrant status, race, and ethnicity (see National Academy of Sciences, Engineering, and Medicine, 2019 for review). The best evidence available suggests that family income is particularly influential in early childhood and for families in the lower end of the income distribution (National Academy of Sciences,

Engineering, and Medicine, 2019). What is less clear is *how* income disparities in young children's development come to be. Research has found that gaps in key cognitive and behavioral skills that emerge in early childhood remain stable through the school years, presaging continuing disparities throughout childhood and into adulthood (Duncan, Magnuson, & Votruba-Drzal, 2017). These patterns suggest the importance of children's early experiences as fundamental mechanisms driving income gaps in children's development (Reardon & Portilla, 2016). As such, a key task for researchers, and the primary goal of this study, is to delineate the contextual forces within young children's primary proximal environments - their families and communities - which contribute to income disparities in developmental outcomes. To this end, we develop and test a conceptual model linking income to child development within a diverse, nationally representative sample of young children in the U.S.

This research is embedded within a bioecological model (Bronfenbrenner & Morris, 2006) which posits that human development is driven by proximal processes - the cumulative experiences and interactions between children and their proximal and more distal environments. For young children, these interactions largely take place within their family context. However, community environments are also expected to play an important role in children's development. This may occur at the microsystem level (Bronfenbrenner & Morris, 2006), as children are directly exposed to community contexts. But for very young children, community environments may function primarily at the mesosystem level, as community forces affect proximal processes within families (Bronfenbrenner & Morris, 2006; Leventhal, Dupéré, & Shuey, 2015).

In this study, we hone in on the manner in which family income is associated with children's development through proximal processes at both community and family levels. In particular, we focus on the potential power of income to buy families into neighborhood

communities they deem desirable, which may in turn support family functioning and thus child development. It is important to note that racially discriminatory policies and practices limit neighborhood choice for families of color (Roscigno et al., 2009; Rothstein, 2017; Turner, 2008). Still, inequality remains a stark reality within communities of color (Kochhar & Cilluffo, 2018), and economic resources bear consequence for the residential location and resulting experiences across diverse families (Henry, Votruba-Drzal & Miller, 2018). With this in mind, we focus in this study on identifying potentially generalizable links between family income and child development. To develop more specific hypotheses within this overarching model of development, we draw on investment and stress theories to identify community and family factors likely to affect children's development.

Investment Models of Income Disparities

Two leading theories drive explanations of how family income is transmitted to children's development. The first, the investment model (Becker, 1991), argues that greater family income enhances the time and money parents invest in children. Such material and psychological resources include those that higher income parents can access at the community level, like quality early educational programs or cultural and recreational experiences (Coley, Votruba-Drzal, Collins, & Miller, 2014; Leventhal, Dupéré, & Shuey, 2015). They also include resources that are provided at the family level, through parents' provision of cognitively enriching and supportive parenting practices (Kalil, Ziol-Guest, Ryan, & Markowitz, 2016).

An extensive body of research documents links between living in a more socioeconomically advantaged neighborhood and children's positive developmental outcomes, but leading scholars highlight the need to unpack this link and elucidate the role of more specific neighborhood resources (Leventhal et al., 2015). Some studies suggest that higher income families may have

greater access to development-enhancing community level investments such as educational and cultural resources. Research has found that high quality early education programs are more available in communities populated by high income families (Burchinal, Nelson, Carlson, & Brooks-Gunn, 2008; Gordon & Chase-Lansdale, 2001). Other research has found that family income is predictive of greater use of formal early education programs (Bassok, Finch, Lee, Reardon, & Waldfogel, 2016; Coley et al., 2014) and of cultural resources such as libraries, museums, and sports programs (Bassok et al., 2016; Kalil et al., 2016). Yet prior research has not carefully assessed whether links between family income and heightened use of community resources are driven by higher income families selecting into communities with greater availability of such resources, which in turn promotes resource use and thus greater enrichment for children; by parental preferences and behaviors which transcend their neighborhood contexts; or through reverse selection processes in which more engaged parents select into higher resourced communities. In short, more evidence is needed concerning the strength and directionality of links between family income, community resource availability, and parenting processes.

At the family level, extant research provides compelling evidence that children in higher income families receive more enriching parenting than their disadvantaged counterparts. Higher income parents have been found to provide greater levels of cognitive enrichment to children, such as book reading, games, and complex language input (Bassok et al., 2016; Kalil et al., 2016; Phillips 2011), and more warm and responsive parenting (Vernon-Feagans et al., 2013; Yeung, Linver, & Brooks-Gunn, 2002). Such parental investments in turn appear to promote young children's development, with numerous prior studies finding that cognitive stimulation is more strongly linked with children's cognitive (versus behavioral) skills and parental warmth more

strongly linked with behavioral (versus cognitive) skills (Bono, Francesconi, Kelly, & Sacker, 2016; Fiorini & Keane, 2014; Gershoff, Aber, Raver, & Lennon, 2007; Price & Kalil, 2018; Vernon-Fagans et al., 2013; Yeung et al., 2002). Yet this work has rarely considered how community contexts may play a role in these processes.

In short, what is missing in much prior research is a careful examination of how the multiple levels of children's proximal and more distal resource environments combine and serve as mediating processes explaining income disparities in children's development (Bronfenbrenner & Morris, 2006). A review of evidence finds limited prior research, which has generally assessed only a piece of this multi-step process. For example, one recent study found that families in higher socioeconomic status (SES) neighborhoods had greater availability of community resources such as medical and educational services, which in turn were associated with less harsh parenting behaviors (Shuey & Leventhal, 2017). Another paper linked neighborhood SES to children's academic skills through parents' provision of cognitively stimulating and supportive parenting behaviors (Dupéré, Leventhal, Crosnoe, & Dion, 2010). Building on this base, we seek to assess a multi-step mediational process linking family income to children's cognitive and behavioral development through community resources and in turn parental investment processes, considering multiple types of resources at both community and family levels. As we consider these questions, it is essential to simultaneously account for the stressors to which children are exposed.

Stress Models of Income Disparities

A second leading theoretical framework explaining how income is transmitted to children derives from the family stress model, which argues that financial strain within families drives children's exposure to stress, disorder, and chaos, which inhibit healthy development (Conger,

Conger, & Martin, 2010; Masarik & Conger, 2017). While this model initially identified household stressors such as parental psychological distress and harsh parenting as key factors affecting children, more recent conceptualizations have highlighted the potential contributions of community level stressors such as concentrated poverty, violence, and environmental pollution to child and family functioning (Evans & Kim, 2013).

With growing economic segregation across American communities, poor families are increasingly exposed to concentrated poverty in their communities (Reardon & Bischoff, 2013). Concentrated neighborhood poverty has been identified as a key community stressor linked to constrained cognitive and behavioral development in early childhood (Carpiano, Lloyd, & Hertzman, 2009; Sampson, Sharkey, & Raudenbush, 2008), with some evidence suggesting that links may function in part through elevated levels of harsh parenting, parental distress, and limited parental stimulation and support (Dupéré et al., 2010; Kohen, Leventhal, Dahinten, & McIntosh, 2008; Odgers, Caspi, Russell, Sampson, Arseneault, & Moffitt, 2012; Vernon-Feagans et al., 2012). This correlational research linking neighborhood and family stress processes is buttressed by a limited body of rigorous experimental and quasi-experimental evidence showing that for poor families, relocating to a more advantaged neighborhood was associated with lowered parental stress (Kling, Liebman, & Katz, 2007) and increased parental engagement (Casciano & Massey, 2012), although mixed links have emerged with harsh parenting practices (Briggs, 1998; Leventhal & Brooks-Gunn, 2003). Although such studies better control for unmeasured bias related to parents' selection into neighborhoods, they conflate shifts in neighborhood characteristics with the stresses of a residential move, and are not able to delineate the particular neighborhood resource or stress processes that may drive effects on parents and children.

Indeed, other types of community stressors have been linked with disparities in family income, including air pollution (Hajat et al., 2013) and violent and property crime (Stucky, Payton, & Ottensmann, 2016). Growing evidence suggests that such contextual stressors may affect young children by overwhelming their physiological response and self-regulation systems (Evans & Kim, 2013; Shonkoff, 2010), in turn impairing both cognitive skills and behavioral regulation (Sharkey, 2010; Sharkey, Tirado-Strayer, Papachristos, & Raver, 2012). Other work suggests that community stressors may be experienced by children mainly through their parents, with neighborhood violence predicting heightened levels of harsh disciplinary practices (Cuartas, 2018) and parental distress (Sharkey et al., 2012). This research has not explicitly linked community violence or disorder to children's functioning through parenting behaviors, although studies with small samples of economically disadvantaged families provide some evidence that parent functioning may serve as a link between such community stressors and children's behavioral development (Coley, Lynch, & Kull, 2015; Linares, Heeren, Bronfman, Zukerman, Augustyn, & Tronick, 2001). Together, this literature suggests the need for greater attention to how specific parenting practices may mediate links between neighborhood stressors and children's development, and whether such pathways are similarly predictive of children's cognitive and behavioral development. Moreover, there is a need to delineate the relative importance of community resources versus community stressors as forces linking family income to children's development.

Research Questions and Contribution

From this broad base of theoretical and empirical evidence, we have developed the conceptual model presented in Figure 1. By combining constructs from multiple theoretical and empirical bases of literature into one holistic conceptual model, we ask: What are the community

and family processes which most strongly explain links between family income and children's cognitive and behavioral skills at age 5 within a nationally representative sample of young children? As shown in our conceptual model, we expect multi-context mediational processes. Specifically, we hypothesize that a) higher family income will be associated with residence in communities with greater educational and cultural resources and lower concentrated disadvantage, crime, and pollution; b) that these community resource and stress processes will be associated with heightened cognitive stimulation and emotional support and lower use of harsh disciplinary practices by parents; and c) that more supportive and less harsh parenting processes in turn will be linked with greater cognitive skills and lower behavioral problems among children. We expect that both resource and stress processes will transmit family income to children, with stronger links between resources and children's cognitive functioning and between stressors and children's behavioral functioning. As shown in the conceptual model, we also test whether community contexts directly relate to children's functioning (bypassing parenting contexts), and whether family income relates to children's functioning directly through parenting (bypassing community contexts). Importantly, our conceptual model proposes that family income will show associations with community and family contexts and child outcomes above and beyond other potentially correlated characteristics of parents and families such as parental education, marital status, immigration status, race and ethnicity, as well as characteristics of children such as birth weight and infant functioning, which we assess through an extensive set of covariates. Through analysis of a nationally representative sample of young children and families, we seek to provide generalizable estimates of the relative strength of these processes across all children in the U.S. to contribute to the knowledge base on how income shapes the contexts children interact with, and thus their development.

Although our conceptual model is derived from a careful review of leading empirical research and theory, it is also essential to assess whether alternate conceptual models may provide a better explanation for associations among our constructs of interest. To evaluate this possibility, we test whether our hypothesized conceptual model provides a better fit to the data and identifies stronger associations than alternate models which hypothesize that a) more effective parents may select into more highly resourced and lower stress neighborhoods, or b) that better resourced and lower stress neighborhoods support economic success and thereby predict later family income. This process will help us identify which model most effectively reflects the processes linking family income and early developmental outcomes.

Although prior research supports pieces of our conceptual model, this work has been largely piecemeal. Prior research has not integrated and directly contrasted resource and stress processes and attended to both proximal family contexts and more distal community contexts to delineate their combined importance for young children's early skills development. By testing this theoretically-based, comprehensive, multi-context model, we seek to inform theoretical frameworks on the transmission of income inequality to child functioning. Results will delineate the contextual factors which serve the strongest role in transmitting income disparities to children, and in turn identify key targets for policy and intervention efforts which aim to improve the life chances of low-income children.

Methods

Sample and Procedures

The sample for this study was drawn from the Early Childhood Longitudinal Study- Birth Cohort (ECLS-B), a nationally representative, multi-method study of roughly 10,700[1] children

[1] Per NCES ECLS-B data reporting requirements, all Ns are rounded to the nearest 50.

born in the U.S. in 2001. The ECLS-B collected data from parents, children, and early childhood education providers/teachers when children were 10 months old (wave 1; 2001-02), 2 years old (wave 2; 2003-04), 4 years old (wave 3; 2005-06), and 5 years old (wave 4; 2006), when most children were entering kindergarten. Response rates for children were 74%, 93%, 91%, and 92% at each respective wave. We incorporated data from direct child assessments and reports from parents and providers/teachers across these four waves of data, thus following children from infancy to age 5. The home zip codes of children at each wave, acquired through a restricted data license, were used to link contextual data from a variety of administrative datasets to children in the ECLS-B sample. Our analytic sample consists of approximately 10,650 children, excluding children who were missing wave 1 zip codes (n <50) or had been diagnosed with a severe disability (n < 50).

Measures

Table 1 presents a brief overview of the source, timing, and definition of each of our primary analytic variables. Table 2 presents descriptive statistics (means and standard deviations or proportions) as well as the level of missing data for all analytic variables.

Family income. Parents reported on total household income in the prior year at each wave. We adjusted income reports to 2006 levels of inflation and averaged over waves 1-3 to create a cumulative measure of income, based on prior research showing greater reliability and predictive validity from cumulative measures (Duncan et al., 2017). To address skew, and because literature shows that links between family income and child development tend to be nonlinear with income mattering more for children from low-income families (Duncan et al., 2017), we transformed income using a natural log.

Community measures. To assess resources (cultural resources and educational resources) and stressors (concentrated disadvantage, crime, and air pollution) in children's community contexts, we linked ECLS-B data with national administrative data using household zip codes from waves 2, 3, and 4, the smallest geographic units released in the ECLS-B restricted data. Much prior research on neighborhood contexts relies on a simple system of using census tracts, zip codes, or respondent perceptions to define neighborhood boundaries (Leventhal et al., 2015). However, other research makes clear that such geographic definitions of neighborhoods may not reliably capture how neighborhood services, experiences, and characteristics are most influential for residents. For example, census tracts and zip codes vary widely in size across the U.S., leading to inconsistencies in geographic scale in national samples combining urban and more rural populations. In addition, different types of neighborhood services and experiences may be influential at different geographic scales. Prior research has found that families often travel miles to access early childhood education programs, for example (Gordon & Chase-Lansdale, 2001). As such, we used Geographic Information Systems (GIS) technology to collate contextual data at the most effective geographic level, following the process described in Miller, Votruba-Drzal, and Coley (2019) to optimize the validity of contextual measures. This process involved aggregating community resource and stress indicators within different radii around the centroid of each child's home zip code and testing predictive validity. For example, to determine the best radii at which to measure cultural resources, we created count variables of all cultural resources (defined below) within each child's zip code, and then within zip codes within 2.5 miles, 5 miles, 10 miles, and 20 miles of the centroid of each child's zip code. We then tested predictive validity of each version of this variable on theoretically-connected variables from the ECLS-B (and engaged in the same process with a different data set assessing children in early elementary

school, the Early Childhood Longitudinal Study- Kindergarten Cohort). In the case of cultural resources, for example, we tested the different geographic versions of cultural resources as predictors of parental reports of how often their child was taken to a library, to a concert, to a museum and to a zoo; we also considered predictive validity to questions such as whether children took part in art lessons, music lessons, or performing arts programs at each wave of the survey. As another example, for measures of violent crime in the neighborhood, we assessed predictive validity to parent perceptions of neighborhood safety and danger. We used these predictive validity checks, as well as prior research and theory, to identify the best radii at which to measure each community construct. To address concerns that measures of community resources and stressors might function differently in densely population urban areas versus more sparsely populated rural areas, we also tested predictive validity across rural, suburban, and urban communities, finding few differences (Miller et al., 2019; Votruba-Drzal, Miller, Coley, & Spielvogel, 2018).

Through this process we identified the optimal geographic scale at which to assess each of our community measures. We created the measures and merged them with each child's address in the ECLS-B at waves 2, 3, and 4. Community variables could change over time because neighborhood characteristics changed, or because families moved: 27% of families moved once and 41% moved more than once across the study period, on average moving to neighborhoods with lower crime, pollution, and concentrated disadvantage, but also with fewer educational and cultural resources than the neighborhoods they were leaving. This high level of residential mobility suggests that studies which assess community characteristics at only one point in time likely mis-specify a holistic view of children's early community contexts. To address this

limitation, we averaged community measures across waves 2 through 4 in order to capture children's community contexts over time and improve measure reliability.

We created two measures of community resources - cultural resources and educational resources - using data from the Economic Census (EC), a national survey that tracks the economic impact of businesses in U.S. zip codes every 5 years, and data from the National Center of Education Statistics (NCES). We linked 2002 EC and NCES data to children's zip codes of residence at wave 2, and linked 2007 data to children's zip codes at waves 3 and 4. To assess cultural resources, we summed the number of cultural and recreational institutions in each zip code, including cultural sites such as museums and historical sites, zoos, performing arts companies, recreational industries, and sports instruction. To assess educational resources, we summed the number of educational support services, early childcare centers, and schools within a 10 mile radius of the centroid of each family's home zip code. To increase normality, we then logged measures of cultural and educational resources.

We also created three measures of community stressors, including concentrated disadvantage, crime, and air pollution. To assess concentrated socioeconomic disadvantage, we drew census tract level data from the 2000 Decennial Census, including the proportion of residents who lived under the poverty line, received public assistance, were unemployed, had not completed high school, or lived in female-headed households. These items were standardized and averaged to create a composite measure of concentrated disadvantage (α=.92), aggregated to the zip code level. This measure was matched to children's zip codes at waves 2, 3, and 4, and then averaged across waves.

We assessed community crime using annual precinct-level data on violent crime obtained from the FBI's Uniform Crime Reporting database. We calculated the violent crime rate (per

10,000 people) using monthly counts of violent offenses including assault, homicide, and sexual assault. We aggregated these data from the precinct level to zip codes within a two-mile radius of each family's home zip code at waves 2, 3, and 4, and then averaged across waves.

Finally, we drew data from the EPA's 2005 National Air Toxics Assessment (NATA), which measures outdoor air quality, to create a measure of air pollution. We used an existing measure that estimates neurological risk associated with breathing air toxins. This measure assessed the concentration of specific air-born chemicals that are associated with adverse effects on the central nervous system at the census-tract level (ICF International, 2011), which we aggregated to each child's zip code at waves 2, 3, and 4 and averaged.

Family processes. We created three measures of family processes using data from waves 2, 3, and 4 of the ECLS-B to assess family level investment (cognitive stimulation and emotional support) and stress (harsh discipline) related processes. Cognitive stimulation was assessed at waves 2, 3, and 4 of the ECLS-B through an array of items drawn from the Short Form of the Home Observation for Measurement of the Environment Inventory (HOME-SF; Bradley & Caldwell, 1979), the National Household Education Survey (NHES), and additional items. Parents reported on a variety of activities including book-reading, singing, and trips to zoos and libraries, with items shifting as children aged. Principal components analyses with promax rotation were used to develop composites at each wave (13 items at waves 2 and 3 and 11 items at wave 4). Composite scores from each wave were standardized and averaged into a composite (α=.82) to increase reliability and capture cognitive stimulation from waves 2 through 4.

Parental emotional support was assessed in the ECLS-B at waves 2 and 3 using the Two Bags Task, a semi-structured direct assessment of parent-child interactions using two play activities that measures parent and child engagement, responsiveness, and negativity and was

designed for use across a broad range of culturally, linguistically, and economically diverse families (Najarian et al., 2010). Parent-child interactions were videotaped and scored by coders provided with extensive training and reliability checks (Narajian et al., 2010). In order to focus on the construct of parental warmth and responsiveness, distinguished from other constructs such as cognitive stimulation, we included the rating of emotional support, scored on a 7-point likert scale from 1 (very low) to 7 (very high), which captured parents' expressions of love, attention, and admiration for the child as well as their responsiveness to their child's cues, needs, and capabilities (Najarian et al., 2010). Scores were averaged across waves 2 and 3.

Harsh discipline was reported by parents at waves 2, 3, and 4 in response to questions concerning whether or not they would engage in an array of disciplinary strategies (e.g., spanking, time-out, talking, chores, etc.) if their child threw a tantrum, yelled, or was aggressive towards them; affirmative responses to options of spanking and hitting children were each coded 1 (versus 0). Parents also reported whether they spanked their child in the last week, also coded 1 versus 0. We summed these three items to create a measure of harsh discipline (Fuller et al., 2009). Harsh discipline measures were standardized and averaged across the three waves (α=.73).

It is important to acknowledge that in addition to capturing distinct domains of parenting, our three parenting measures were drawn from different sources (parent report versus direct observation), and captured quality versus frequency of parenting practices. These different sources and foci may have implications for the construct and predictive validity of the measures, driven by reporter or observer bias as well as the distributional properties of the measures (Aspald & Gardner, 2003; Herbers, Garcia & Obradović, 2017; Najarian et al., 2010).

Child skills. Children's reading and math skills were assessed in the ECLS-B study at wave 4 with direct assessments, designed to accommodate children with varying abilities. Children were screened for basic English proficiency using items from the PreLAS 2000 (Duncan & De Avila, 1998) and the Peabody Picture Vocabulary Test Third Edition (PPVT-III) (Dunn & Dunn, 1997), and assessments were thereafter conducted in English or Spanish, although so few children were routed into the Spanish version that all scored and released wave 4 child assessment data were collected in English (Najarian et al., 2010). ECLS-B cognitive assessments contained items drawn from well-validated instruments including the PreLAS, PPVT-III, the Preschool Comprehensive Test of Phonological & Print Processing (Lonigan, Wagner, Torgesen, & Rashotte, 2003), and the Test of Early Mathematics Ability (3rd ed.; Ginsburg & Baroody, 2003), as well as from the Family and Child Experiences Survey (FACES), the Head Start Impact Study, the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99 (ECLS-K), and items developed for the ECLS-B.

The reading assessment focused on both language and literacy, measuring word recognition, letter sounds, and phonological awareness; reading comprehension and interpretation; and receptive and expressive vocabulary. The direct assessment of math tested number sense, properties, and operations; measurement; geometry and spatial sense; data analysis, statistics, and probability; and patterns, algebra, and functions. IRT scale scores were created to assess children's performance relative to their peers, leading to highly reliable scores (α=.92 for reading and math). We created a cognitive composite by standardizing and averaging children's scores on reading and math, which were highly correlated (r=.82).

Children's behavioral functioning was assessed in the ECLS-B through teacher and parent reports, using items drawn from the Preschool and Kindergarten Behavior Scales-Second Edition

(PKBS-2), the Social Skills Rating System (Gresham & Elliott, 1990), and adapted for the ECLS-B. Because we were particularly interested in children's success as they entered formal schooling and because prior research has found that teacher reports may show stronger reliability and validity than parent reports on measures of problem behaviors (Stone, Otten, Engels, Vermulst, & Janssens, 2010), we focused on teacher reports. Kindergarten or early childhood education teachers reported on children's externalizing behavior problems at wave 4, indicating how often on a scale of 1 (never) to 5 (very often) the child displayed antisocial and impulsive behavior (e.g., being aggressive; acting in a disruptive manner). Seven items tapping into these behaviors were averaged to create the externalizing scale (α =.88).

Covariates. It is essential to acknowledge the plethora of structural and personal forces which may systematically impede or support family income, neighborhood selection, and parenting practices as well as children's development. Although we cannot definitively adjust for all such forces in correlational research, we included a rich set of child and family covariates to help isolate the role of family income from related child, parent, and family characteristics and adjust for measured factors that may differentially select families into income strata and communities through external forces such as racial discrimination or internal forces such as preferences, as well as affect parenting behaviors and children's development. Time-invariant covariates (e.g., child race/ethnicity and sex) were drawn from wave 1; covariates related to child experience (e.g., months in kindergarten and age at assessment) were drawn from wave 4; and time-varying covariates were drawn from each wave. Child level controls included sex (male or female), race and ethnicity (White; Black; Asian, Hawaiian, or Pacific Islander; Hispanic of any race; American Indian or Alaskan Native; or multiple races/other race), age at assessment, and months in kindergarten at wave 4. To help adjust for perinatal or genetic

individual differences that may be correlated with family income, children's contexts, and child outcomes, we also included low birth weight status (i.e., whether the child was less than 2500 grams at birth), wave 1 temperament (assessed using 15 items from the Infant/Toddler Symptom Checklist [DeGangi, Poisson, Sickel, & Wiener, 1995] and the Behavior Rating Scale [Bayley, 1993]; α=.70), and wave 1 cognitive skills (assessed using the Bayley Short Form Research Edition [National Center for Education Statistics, 2000]; α=.80).

Parental covariates included maternal age and parent immigrant status (i.e., whether at least one parent was born outside the US), primary language used at home (non-English across waves, non-English at some point, or English across waves), mother's marital status (married across waves, single across waves, or change in marital status), the number of children in the household (averaged across waves), and the number of residential moves (summed across waves). We also included parent education (coded categorically as below high school, high school or equivalent, some college, bachelor's degree, or graduate or professional degree to allow for nonlinear effects), which captured the highest level of education of either parent and was coded to reflect the educational status that was reported for the majority of waves (or the most recent wave, in the case of an even split). We also included geographic region (South, Midwest, Northeast, or West) in which the family resided for the majority of the waves (or, in the case of an even split, their most recent region of residence). We assessed all continuous variables for normality, and log-transformed non-normal variables.

Variables used in additional specifications. As detailed below, we estimated a number of alternate model specifications to test the robustness of our results and compare model fit across different conceptual models. These alternate models incorporated additional or alternately coded variables, including the following. A measure of maternal psychological distress, assessed using

items from the Center for Epidemiological Studies-Depression Scale (CES-D; Radloff, 1977), averaged across waves 1, 3 and 4 (α = .89), was included as an additional measure of family stress. An SES composite, created by standardizing and averaging parental reports of income, a continuous measure of years of education, and a continuous measure of job prestige, averaged over waves 1 through 3, was assessed in replacement of family income. Finally, alternate versions of family income, community contexts, and family processes were created by averaging each measure over waves 1 through 4.

Data Analysis

Missing data. Missing data on variables ranged from 0% to 57% across all variables included in analyses drawn from waves 1 through 4, with higher levels of missing data at later waves due to sample attrition (see Table 2 for levels of missing data for each analytic variable). In order to limit bias from missing data, we imputed missing data on all variables to create 30 complete datasets using the Amelia II package in R, which uses a bootstrap-based Expectation-Maximization algorithm to impute missing values (Honaker, King & Blackwell, 2018), leading to complete data for all 10,650 children across waves 1, 2, 3, and 4. Comparisons of pre/post imputation descriptive statistics on our analytic sample demonstrated a high degree of consistency for both categorical and continuous variables. Following data imputation, we created cross-wave composite measures as delineated in the measures section above and summarized in Table 1.

Data analysis. We tested our conceptual model using structural equation modeling in Mplus 8.2 to assess associations between family income, community resources and stressors, family processes, and children's skills (see Figure 1). Separate models were estimated for children's cognitive skills and behavioral problems. Our measurement decisions were designed

to balance the goals of improving measurement reliability and capturing children's environments over time through the use of multi-wave contextual measures with the goals of assessing temporal precedence and limiting possible bias from reverse causation. As such, our main models incorporated waves 1-3 family income, waves 2-4 community resources and stressors and family processes, and wave 4 children's skills. To provide further evidence related to temporal ordering and potential reverse causation, we estimated a number of alternate model specifications (details presented in Results section).

To help minimize unmeasured heterogeneity bias (the bias that may occur when observed associations between key study variables are driven by underlying differences; Xie, 2011) and selection bias (the bias from participants "selecting into" conditions such as income strata or neighborhood contexts; Leventhal & Brooks-Gunn, 2000), we included a broad range of covariates drawn from prior literature. Cross-wave composites from waves 1 through 3 predicted income, while cross-wave composites from waves 2 through 4 predicted community and family processes and child outcomes. The inclusion of these covariates helps to isolate unique associations between our primary variables of interest and assuage concerns that unmeasured forces are driving our results, although it is essential to note that our models remain correlational and cannot identify causal relationships.

To mitigate potential concerns over multicollinearity, we confirmed that bivariate correlations among community measures (r = -.04 to .65) and among family measures (r = -.16 to .39) were within acceptable ranges. Analytic models included covariances between all community resource and stress measures, and between family process measures. It is important to note that multilevel models were not appropriate for these data both because of low levels of clustering and because nesting units changed over time, with 68% of children moving at least

once over the study period. All models included clustered standard errors at wave 1 zip codes to adjust for the modest geographic clustering of children, and wave 1 parent sampling weights (W1R0) to ensure that results generalized to a nationally representative sample of children born in the U.S. in 2001.

MPlus calculates parameter estimates with multiply imputed data using Rubin's Rules, which compute standard errors using the average of the squared standard errors and the between analysis parameter estimate variation (Rubin, 1987). To calculate and test the significance of indirect effects we used the Delta method (through the "model indirect" command in MPlus), which adjusts for the covariance between path estimates, although when using continuous observed variables this covariance term is approximately 0 and hence the delta method parallels the Sobel indirect test (MacKinnon, 2008). We assessed model fit using the Root Mean Square Error of Approximation (RMSEA), an absolute fit index with recommended thresholds for a good fit below .05, and the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI), incremental fit indices that have recommended thresholds above .95 (Cangur & Ercan, 2015). In order to develop the most parsimonious models, we pared non-significant pathways between our primary variables of interest, which led to improved model fit and minimal shifts in path coefficients. Hence we present the final trimmed models.

Results

Descriptive Results

Weighted descriptive data on the analytic sample are presented in Table 2. Children in the sample averaged approximately five and a half years old and had spent 2 months in kindergarten at wave 4 data collection. About half were female (49%), and a relatively small portion were born low birth weight (7%). Fifty-three percent of children were non-Hispanic White, 25%

Hispanic, 14% non-Hispanic Black, 3% Asian, Hawaiian, or Pacific Islander, 1% American Indian or Alaskan Native, and 4% multiple races or other race.

Caregivers in the sample were 33 years old on average, were most often stably married (64%) across waves, and had between 2 and 3 children in the home. Families had an average income of $58,000 and some college education (30%). Roughly a fourth of the sample children (24%) had at least one immigrant parent, and 18% primarily spoke a language other than English at home across waves. The sample was spread across the US, with the highest portion in the South (38%).

Structural Equation Model Results

Table 3 presents standardized coefficients, which are interpreted as effect sizes and allow us to compare the size of the effects across paths within and across models, and standard errors for the primary paths from the final trimmed structural equation models predicting children's cognitive skills and children's externalizing behavior problems. (Covariate paths not shown; available by request.) To aid interpretation, we also present results pictorially in Figures 2 and 3. These figures show the statistically significant paths noted in Table 3, along with standardized coefficients for each of these paths, to visually highlight the primary mediating forces identified in the complex structural equation models. In order to understand how community and family resource and stress variables mediate the links between family income and children's functioning, we present direct, indirect, and total effect estimates in Table 4. Trimmed models showed excellent fit to the data (cognitive skills model: RMSEA 0.014, CFI 0.986, TLI 0.960; externalizing problems model: RMSEA 0.014, CFI 0.985, TLI 0.958).

Family income to community resources and stressors. Starting from the left of the models, results indicate that, as hypothesized, family income was significantly associated with

heightened community resources and lower community stressors, with small effect sizes. Specifically, a 1 standard deviation (SD) difference in family income predicted .25 SD greater educational resources and .20 SD greater cultural resources. Family income also predicted .34 SD lower concentrated disadvantage and .10 SD lower violent crime rates. In contrast, the link between family income and air pollution was not statistically significant.

Predictors of family processes. Turning to the next set of paths in the models, results show that community resources and stressors were significantly associated with family processes with small effect sizes. Educational resources predicted heightened levels of cognitive stimulation (.05 SD) as well as lower harsh discipline (.08 SD), but were not significantly associated with parents' emotional support. Cultural resources were associated with all three aspects of parenting, predicting heightened cognitive stimulation and emotional support as well as lower harsh discipline, all with effect sizes of .04 SD.

Considering community stressors, results show consistent associations between concentrated disadvantage and family processes. Concentrated disadvantage was associated with lower cognitive stimulation (.06 SD), lower emotional support (.07 SD), and heightened harsh discipline (.06 SD). In contrast, community violent crime rates only predicted greater harsh discipline (.04 SD), while air pollution showed no significant associations with any of the family process variables. In addition to these links between community and family processes, we also found that family income retained direct connections to heightened cognitive stimulation (.10 SD) and emotional support (.11 SD) as well as lower harsh discipline (.07 SD).

Predictors of children's cognitive skills. Turning to predictors of child functioning presented in the bottom panel of Table 3, results show patterns implicating both resource and stress processes. Both cognitive stimulation and emotional support predicted heightened

cognitive skills among children, with effect sizes of .16 SD and .07 SD respectively. Above and beyond these proximal links, we identified a direct positive link between educational resources and cognitive skills, as well as a direct negative link between air pollution and cognitive skills (both .04 SD). Finally, family income retained a significant direct link with children's cognitive skills (.13 SD).

Together, these paths led to several significant indirect effects through which family income was associated with children's cognitive skills, as shown in Table 4. Indirect effects ran from family income through both community resources and stressors, but through only investment-related parenting processes to children's cognitive skills. Specifically, significant indirect paths ran from family income to greater community educational and cultural resources and then through heightened parental cognitive stimulation to children's enhanced cognitive skills. Significant indirect paths also ran from income through greater cultural resources and then enhanced parental emotional support, as well as directly from income through heightened parental cognitive stimulation and parental emotional support to children's enhanced cognitive skills. Finally, we identified significant indirect paths from income through lower community concentrated disadvantage and then greater parental cognitive stimulation and emotional support to children's enhanced cognitive skills. Despite these significant mediational paths, a direct link between income and children's cognitive skills remained significant.

Predictors of children's behavior problems. Turning to predictors of children's behavior problems, different patterns of indirect effects emerged, with effects running through community resources and stressors as well as both stimulating and harsh parenting processes. Model parameters in Table 3 show that parents' provision of cognitive stimulation predicted lower behavior problems among children (.10 SD), whereas harsh discipline predicted heightened

behavior problems (.08 SD). Concentrated neighborhood disadvantage was the only community level variable that retained a significant direct link with behavior problems (.04 SD), although surprisingly, this association was negative, with greater concentrated disadvantage predicting lower behavior problems.

Turning to indirect effects (Table 4), paralleling results for cognitive skills, we identified significant indirect effects from family income to lower behavior problems running through educational resources, cultural resources, and concentrated disadvantage and then cognitive stimulation. Parents' harsh discipline also played an important role for children's behavioral functioning, with indirect paths identified from family income through heightened educational and cultural resources, as well as lower concentrated disadvantage and violent crime to lower harsh discipline and then decreased behavior problems. Additional significant indirect paths ran from income to heightened cognitive stimulation and lower harsh discipline and then to lower behavior problems (bypassing community contexts).

Alternate model specifications. We conducted a rich set of additional model specifications that included additional variables, alternative versions of variables, and alternative conceptual models. (Results for all alternative models available upon request.) First, we compared models using family income to those using a family SES composite (including parental income, education, and job prestige). Findings were largely parallel, though model fit declined slightly, with the BIC rising from 161,009.499 to 161,510.999 for cognitive skills and 172,537.853 to 172,971.281 for externalizing behaviors. This supported our decision to focus on parental income for its clearer practical significance. Second, reflecting the family stress model and related literature (Conger et al., 2010; Masarik & Conger, 2017), we estimated models including maternal psychological distress as an additional family process, and separately as a

predictor of other family processes. Model fit improved in both cases, with the BIC dropping from 189,204.911 to 186,060.064 for cognitive skills and from 190,327.924 to 187,136.86 for externalizing problems. However, no significant links emerged between community contexts and maternal psychological distress, nor indirect effects running through these variables, and hence this construct was excluded in the main models. Third, we estimated models using measures of family income, community contexts, and parenting processes using all available data from waves 1-4. Results were similar to those presented in the main models, which have the added advantage of temporal precedence. Model fit was weaker for these alternatives, with the BIC rising from 174,282.763 to 191,065.72 for cognitive skills and from 175,481.370 to 192,195.475 for externalizing skills.

More important conceptually, the fourth and fifth sets of alternate model specifications were estimated to test the power of different selection processes through alternate conceptual models. The fourth assessed the argument that more engaged parents may select into more supportive neighborhoods by testing a model in which income predicted parenting processes, which in turn predicted community resource and stress variables and then child outcomes. The BIC rose from 174,282.763 to 193,172.780 for cognitive skills and from 175,481.370 to 194,362.141 for externalizing problems models, and none of the paths from the three parenting process variables to the five neighborhood resource and stress variables were significant, suggesting no evidence in support of this conceptual model. A fifth alternative assessed the argument that neighborhood contexts may affect family income by estimating a model in which neighborhood resource and stress variables predicted family income, which in turn predicted parenting processes and hence child outcomes. Again, the BIC increased (from 174,282.760 to 190,483.366 for cognitive skills and from 175,481.370 to 191,673.867 for externalizing

problems), and path coefficients between neighborhood variables and family income decreased in size, with decreases of approximately 50% to 100%. We interpret these results as suggesting that there may be some bidirectional associations between family income and neighborhood contexts, with higher income families selecting into more resourced and less stressed neighborhoods, but also, to a lesser degree, with more resourced and less stressed neighborhoods promoting higher family income.

Discussion

Growing economic disparities between American families and the increased sorting of families into economically segregated communities have heightened the need to clearly delineate the pathways through which family income promotes children's development and hence transmits advantage and disadvantage across generations. Assessing a nationally representative sample of children followed from infancy through age 5 and their families, matched with a broad array of contextual data, this work provides new evidence of how community and family processes may together underlie the transmission of income inequality, supporting both investment and stress frameworks. Although pieces of our conceptual model have been tested in prior research, this work expands extant knowledge in key ways. Contributions range from *theoretical* (combining constructs from both investment and stress theories into one holistic model,), to *methodological* (developing and validating measures of community resources and stressor from multiple datasets, with the geographic scale of each variable validated across two distinct datasets and across urbanicity strata), to *empirical* ((through provision of evidence that links between family income and young children's development run through community forces become meaningful to children through their links with proximal processes at the family level, and that this conceptual model was far superior to alternates). By considering a broad array of

community and family level measures, this study sought to more carefully identify the relative importance of different contextual forces for children's cognitive and behavioral functioning, to clarify how these contextual forces work in conjunction with one another, and to assess the directionality and temporal ordering of these relations. Prior research has found that income has causal implications for child development (National Academy of Sciences, Engineering, and Medicine, 2019). The present research contributes to our understanding of *why* income matters, which can in turn inform the development of targeted policies and practices seeking to disrupt enduring economic inequities.

Results from this study highlight three key lessons. First, lower-income children were shown to have more limited access to community resources and heightened exposure to community stressors compared to their higher income counterparts. Second, community resources and stressors were significantly associated with both engaged and punitive parenting processes. And third, both community contexts and family processes served as key mediators linking family income to children's cognitive and behavioral functioning. In considering the results from this study, it is essential to acknowledge the correlational nature of the data and the small effect sizes unearthed in our complex, multi-context models linking family income to young children's cognitive and behavioral skills.

Family Income Links with Community Resources and Stressors

One of the primary contributions of this work lies in the unique direct modeling of how family income is associated with families' selection into neighborhoods (adjusting for a broad array of child, parent, and family covariates) and identification of heightened community resources surrounding higher versus lower income families. Using innovative measures to capture the prevalence of educational and cultural resources in proximity to families' homes, we

found that higher income families tend to live in communities richer in such services. Although prior research has documented the increasing economic segregation of school districts (Owens et al., 2016) and higher income families' greater use of high quality educational and cultural resources (Bradley & Corwyn, 2004; Dupéré et al., 2010; Kornrich & Fursentburg, 2013), this is the first work of which we are aware to document notable disparities in availability of such resources using a nationally representative sample of young children and validated geographic measures. Replicating past work (Hajat et al., 2013; Reardon & Bischoff, 2013; Stucky et al., 2016), we also found that higher income families lived in communities with lower concentrations of disadvantage and lower violent crime rates. With non-experimental data it is impossible to fully explicate the causal processes behind these connections. But importantly, by directly testing alternate model specifications, we extended prior correlational evidence by finding far stronger support for the hypothesis that higher levels of income allow families to select into more resourced and less stressed neighborhoods than for the hypothesis that neighborhood contexts drive family income. Future research may seek to more directly assess such bidirectional processes and to consider parents' knowledge of and families' direct exposure to both resources and stressors in their communities.

It is essential to acknowledge that the selection of families into neighborhood is driven not only by family economic resources and preferences, but also by forces that may be beyond families' control. As previously noted, there is a long history of racial stratification in the U.S. that has resulted in uneven access to prosperous, safe communities, with predominantly Black and Latinx neighborhoods experiencing high levels of disinvestment at the same time that Black and Latinx families were being systematically excluded from higher resourced communities (Dreier, Mollenkopf & Swanstrom, 2014; Rothstein, 2017). Not only does this legacy help

explain the uneven distribution of community resources and stressors across U.S. neighborhoods; it also means that income may have less "buying power" for families affected by historical and ongoing racial oppression (Henry et al., 2019). Although there is good reason to believe that access to economic capital is important for all families (National Academy of Sciences, Engineering, and Medicine, 2019), there is also a clear need to understand the unique ways that income and income inequality operate within and across different racial and ethnic groups. This is a key area for future research.

Community and Family Processes: Within-Construct and Cross-Construct Links

A second key set of results from this work identified both within-construct and cross-construct links between community and family resource and stress processes, which, albeit small in size, served as mediators linking family income to children's functioning. The most consistent paths found that greater availability of community educational and cultural resources as well as lower levels of concentrated community disadvantage were associated with more cognitively stimulating and emotionally supportive, and less harsh parenting practices, and in turn with children's cognitive and behavioral functioning. The consistency of these results is notable, suggesting that community socioeconomic and institutional resources may facilitate parents' ability to provide responsive and enriching parenting. Our results expand prior research by delineating how these community and family processes serve as multi-step mediators linking family income to children's early development.

Community resources such as educational programs, museums, and zoos may support enriching parenting and limit harsh disciplinary practices by providing access to experiences in which parents can stimulate and support children; examples of responsive and enriched interactions with children; and assets which may limit parental stress. These mechanisms have

been identified in more targeted prior research. For example, Small (2006) argues that childcare centers function as cultural brokers for families, connecting them to the services they need to support their child's development. Further, Bell and colleagues (2009) suggest that cultural spaces like zoos and museums are often designed to stimulate and support parent-child learning, whereas stress researchers argue that access to these types of resources may decrease parent physiological stress, in turn promoting positive parenting practices and child outcomes (McEwen & McEwen, 2017). In contrast, concentrated community disadvantage may increase parental stress, inhibit social support, and limit exposure to scaffolded parent-child experiences and enriched interactions, thereby constraining parents' ability to provide supportive parenting (Kohen et al., 2008; Leventhal & Brooks-Gunn, 2003). Importantly, the current study extends prior work by providing evidence that multiple types of neighborhood resources and stressors were each uniquely associated with stimulating, supportive, and harsh parenting processes. Moreover, by comparing alternative models, we were able to explicitly test and reject the argument that more effective and engaged parents selected into higher resourced and less stressed neighborhoods. Although further experimental research is essential for showing causal evidence, these results suggest that enhancing poor families' access to enriching educational and cultural services and programs, through neighborhood economic integration or the targeted development of such services in low-income communities, may be a key mechanisms for supporting quality parenting and young children's development.

In contrast to the broad role of socioeconomic and institutional resources at the community level, other community stressors showed more circumscribed roles. Specifically, our results highlight links between community violent crime and harsh parental disciplinary practices such as spanking, which were linked with children's behavioral but not cognitive outcomes.

Expanding prior work that has similarly identified links between neighborhood violence and parental stress but not positive parent investment processes (Coley et al., 2015; Cuartas, 2018; Sharkey et al., 2012; Linares et al., 2001), these results raise concerns about the intergenerational transmission of aggressive behaviors (Coley, Kull & Carrano, 2014; Flouri & Midouhas, 2017; Gershoff & Grogan-Kaylor, 2016). It is important for further research to delineate whether the connections between community crime and elevated harsh discipline practices are driven by parental stress, parents' efforts to protect children from dangerous environments, or other forces. For instance, harsh disciplinary practices may be connected to parents' prior traumatic experiences within the criminal justice system, which are likely to be more common in poor, over-policed communities (Alexander, 2012).

In contrast to the other community context measures, our results found that community pollution played a limited role in our model linking family income to children's development. Although the NATA neurological risk measure of air pollution was directly associated with decreased cognitive skills among children, we found no significant associations with family income, nor with parenting processes. These results support recent findings that not all types of pollution are heightened in disadvantaged communities across all geographic spaces (e.g., Hajat et al., 2013; Wilhelm, Qian, & Ritz, 2009). Together, results suggest the need for continued work on how air pollution and other environmental stressors such as water pollution, allergens, and housing disorder may play a role in transmitting economic disadvantage to children's healthy development.

In addition to the limited role of violent crime and air pollution, one surprising finding that emerged in our results was a small direct connection between higher community concentrated disadvantage and lower child behavior problems. The meaning behind this unexpected

association remains unclear. One possibility is that, after adjusting for the manner in which concentrated disadvantage interrupts productive parenting and is correlated with other community stressors and resources, such levels of disadvantage may constrain children's externalizing behaviors. However, additional exploratory models that removed the other community variables replicated this pattern of results, implying that covariances between community constructs were not the driving force behind this result. It may thus be that growing up in concentrated disadvantage encourages young children to conform to behavioral expectations, perhaps through heightened parental monitoring and control or because acting out has heightened consequences in this context. Another possible explanation comes from recent evidence with adolescent samples which has found that adolescents in affluent neighborhoods or affluent schools show a greater likelihood of engagement in externalizing behaviors such as substance use and property crime (Coley, Sims, Dearing & Spielvogel, 2018; Lund & Dearing, 2013), perhaps in response to limited parental engagement and peer and academic stressors (Luthar, Barkin & Crossman, 2013). Future research should consider whether affluent contexts provide unique challenges for young children, and should further explore the unique strengths of children, families, and communities facing concentrated disadvantage.

Expanding Theory on how Family Income is Transmitted to Children's Development

In sum, the results of this study expand prior theory and research highlighting the important role of both resource and stress processes as key forces linking family income and young children's cognitive and behavioral development in a comprehensive model with innovative community measures, using nationally representative data. By explicating links between processes at the community *and* family levels with children's cognitive *and* behavioral functioning, our results provide support for the bioecological model of human development,

which underscores the complex, nested contextual forces affecting human development (Bronfenbrenner & Morris, 2006). Results further support newer theoretical arguments that view stress and resource processes as functioning across domains of human development, such as models which highlight how stress can affect physiological and neurological processes which inhibit both cognitive growth and behavioral control (Shonkoff, 2010; 2012). An important area for future research is to assess how these diverse contextual forces may interact. Ample and accessible educational and cultural programs, for example, may prove particularly important for children with limited stimulation in their home environments, while parental sensitivity and stimulation may help to protect children in the face of community violence and concentrated poverty.

Additional directions for future research include the need to address whether the processes we identified function similarly or differently across diverse contexts, such as urban versus rural communities, and among different populations, including across racial and ethnic groups. For example, a recent paper (Miller et al., 2019) assessed how community resources and stressors differed in the communities inhabited by poor children across rural, suburban, and urban communities across the U.S. This research identified higher levels of resources such as social services, cultural institutions, and parks in more urbanized communities, in addition to higher levels of crime and concentrated poverty. These resources and stressors appeared to counteract each other, helping to explain limited differences in the cognitive skills of poor school-age children across urban, suburban, and rural communities. Another important future direction is further work delineating the relative roles of different aspects of socioeconomic status on child development, such as educational attainment and family wealth. Recent research, for example,

suggests that educational disparities in early academic skills show distinct patterns from income disparities across racial groups (Henry, Betancur Cortés, & Votruba-Drzal, 2020).

Indeed, because economic inequality is overlayed by enduring racial and ethnic stratification in the U.S., several pieces of our conceptual model may operate in different ways for White, Black, Latinx, Indigenous, and Asian families, as well as for different communities within each pan-ethnic category (Henry, Votruba-Drzal & Miller, 2019). Due to systems of power and privilege as well as diverse cultural forces, families of distinct racial and ethnic groups may experience different supports and challenges in their proximal contexts, affecting how family income is transmitted to children's wellbeing (Henry et al., 2019).

The role of racial and ethnic discrimination is particularly essential factor to consider further, as both structural racism and interpersonal bias and discrimination may affect all pieces of our conceptual model. Both scholarship and public attention have increasingly turned to the ongoing and pernicious impacts of racism and discrimination that flow through policies and practices affecting housing, employment, and school opportunities as well as interpersonal interactions across all of these settings. A long history of racist housing practices such as redlining, exclusionary covenants, and public housing policies, for example, have constrained families' of color, particularly Black families' choices in residential location, driving many into under-resourced and high stress communities. Such forces have grossly limited the development of wealth at the family level and perpetuated cycles of economic disinvestment, criminalization, and over-policing at the community level, both of which contribute to the intergenerational transmission of disadvantage among Black and other families of color (Alexander, 2012; Rothstein, 2017; Turner, 2008). Racism and discrimination further have been shown to impact children and parents through day-to-day experiences that, over time, can raise physiological

stress responses and impair functioning in numerous domains (Berger & Sarnyai, 2014; Hope, Hoggard & Thomas, 2015; Sawyer, Major, Casad, Townsend & Berry Mendes, 2012). Although our goal in this study was to identify generalizable community- and family-level pathways through which income may be translated to children across a nationally-representative sample of children, it is essential for future research to delve deeply into how such processes may vary across racial and ethnic subgroups facing disparate opportunities and constraints. Such investigations are a critical step for more fully interrogating how intersecting modes of social stratification impact development.

Limitations

In considering the implications of this work, it is critical to note myriad limitations, perhaps most importantly the correlational nature of the data and the consistently small effect sizes of measured relationships. Concerns over selection and unmeasured heterogeneity bias that accompany non-experimental research necessitate caution and limit causal interpretations. As with all correlational research assessing neighborhoods and families, results may be affected by simultaneity bias (wherein families affect neighborhood contexts at the same time that neighborhoods affect families, e.g., Formoso, Weber & Atkins, 2010); omitted variable bias (failing to include correlated features of neighborhoods or families that are the true cause of observed relations); or other types of selection bias and endogeneity (not fully capturing factors which affect families' selection into neighborhoods; Leventhal et al., 2015). We attempted to address these concerns, using alternate reverse causation models to assess simultaneity bias, and inclusion of a rich set of child, parent, family, and contextual covariates embedded in a conservative modeling strategy to address endogeneity and selection bias.

Nonetheless, it is not possible to adjust for all potential biasing factors in correlational research. It is likely that unmeasured factors such as parental preferences or family wealth, for example, may play a role in higher and lower income families' selection into neighborhood contexts as well as in parenting behaviors and children's development. Contextually, measures tapping into the quality of cultural and educational resources or the frequency with which families access such resources were not available, and we did not have measures of other types of resources that may be particularly influential for some families, such as religious organizations. Similarly, stressors such as housing disorder and racial and ethnic discrimination were not assessed.

It is important also to reiterate the small effect sizes unearthed in our results, which may be explained by several factors. For one thing, measurement error and imprecision are inevitable in quantitative research, and these issues may have been elevated by our use of large-scale administrative data and self-report measures. For instance, the FBI crime data had substantial missing data due to precincts failing to submit voluntary reports, and for precincts that did submit reports, the locations where crime occurred were not necessarily matched with the precinct in which they were reported. Similarly, the fact that the restricted ECLS-B data includes children's zip codes of residence but not more targeted geographic identifiers like census tracts or blocks meant that our community measures were matched to a relatively large geographic scale. Meanwhile, parent reports of both income and parenting behaviors, observations of parenting behaviors, and teacher reports of children's externalizing behaviors may have been affected by reporter bias. The emergence of associations *despite* these limitations points to the likely practical significance of these effects.

Beyond issues of measurement, given that we assessed an array of distinct but correlated community and family factors simultaneously, small effect sizes are unsurprising. This is because we parsed variance among a multitude of mediating processes rather than assessing single constructs, such as neighborhood disadvantage, which are often used to proxy for a wide array of underlying specific processes (Kling et al., 2007; Leventhal et al., 2015). As such, comparatively small effect sizes likely reflect the higher level of specificity sought in the present models. Moreover, it is important to reiterate that our data assessed a cohort of children born in 2001. Given the increasing income inequality and expanding economic segregation of neighborhoods that has occurred in recent decades (Bradbury & Triest, 2016; Reardon & Bischoff, 2013), it is possible that the associations we identified have strengthened over time. Finally, it is worth noting that families and children live complex, multi-dimensional lives. Though we examined a wide array of factors that are theoretically connected to the transmission of income to child development, these factors capture only a small piece of a much larger picture.

Implications and Conclusions

Beyond these limitations, it is important to reiterate the contributions of this rich, process-oriented research that sought to map multi-contextual pathways linking family income to young children's development. As recent studies such as Moving to Opportunity and the Head Start Impact Study have shown, controlled experiments on complex social phenomenon show a host of practical, interpretative, and validity challenges (Chetty, Hendren & Katz, 2016; Leventhal & Brooks-Gunn, 2003; Puma et al., 2010). Such challenges highlight the continued importance of complex, theoretically-driven descriptive research such as the present work.

In summary, this study provides support and specificity for leading theoretical frameworks that argue that access to enriching resources and limited exposure to stressors may serve as key processes transmitting family economic resources to young children and driving the intergenerational transmission of advantage and disadvantage. Given the stability in income gaps in children's skills once they enter primary school (Duncan et al., 2017), these results suggest the need for additional policy mechanisms to support low-income children's early development. The most obvious potential policy target is income inequality itself. A recent National Academy of Sciences, Engineering, and Medicine (2019) report provides ample targets for policy shifts to reduce child poverty and decrease income inequality in the U.S.

Our results suggest numerous other targets for interrupting the transmission of inequality to young children. Much more could be done to increase low-income families' access to better resourced and safer neighborhoods. Results from housing mobility studies highlight the improved life chances of poor children who have the opportunity to move to higher resourced neighborhoods, although they also identify continued barriers grounded in racism, discrimination, limited social support, and mismatched norms and preferences that can impede successful economic integration of neighborhoods (Chetty et al., 2016; Owens & Clampet-Lundquist, 2017). Such findings highlight the need for additional efforts to improve low-income families' access to enriching community resources and to reduce crime and pollution within the communities in which they live. Moreover, our results point to the need for mechanisms to increase low-income children's access to stimulating learning materials and to responsive and warm caregiving. The federal Maternal, Infant, and Early Childhood Home Visiting program, for example, is funding numerous models of evidence-based home visiting and parent support programs which been shown to improve home environments, increase sensitive parenting, and

decrease use of harsh discipline practices among at-risk families (Michalopoulos et al., 2019). Expansion of efforts targeting multiple aspects of children's proximal contexts can all contribute to increasing the early skills, and hence life chances, of children in low-income families.

References

Alexander, M. (2012). *The New Jim Crow*. New York: The New Press.

Asante Muhammad, D., Tec, R., & Ramirez, K. (2019, November 18). *Racial wealth snapshot: American Indians/Native Americans.* National Community Reinvestment Coalition. https://ncrc.org/racial-wealth-snapshot-american-indians-native-americans/

Aspald, H. & Gardner, F. (2003). Observational measures of parent-child interaction: An introductory review. *Child and Adolescent Mental Health, 8*, 136-143.

Bassok, D., Finch, J. E., Lee, R., Reardon, S. F., & Waldfogel, J. (2016). Socioeconomic gaps in early childhood experiences: 1998 to 2010. *AERA Open, 2*(3), 1-22.

Bayley, N. (1993). *Bayley Scales of Infant Development*. London, UK: Pearson Assessment.

Becker, G. S. (1991). *A treatise on the family*. Cambridge, MA: Harvard University Press.

Bell, P., Lewenstein, B., Shouse, A., & Feder, M. A. (2009). *Learning science in informal environments: People, places and pursuits*. Washington, DC: National Academies Press.

Berger, M., & Sarnyai, Z. (2015). "More than skin deep": stress neurobiology and mental health consequences of racial discrimination. *Stress*, *18*(1), 1-10.

Bischoff, K. & Reardon, S. F. (2014). Residential segregation by income, 1970-2009. In J. Logan (Ed.), *Diversity and disparities: America enters a new century* (pp. 208-233). New York: Russel Sage Foundation.

Bono, E. D., Francesconi, M., Kelly, Y., & Sacker, A. (2016). Early maternal time investment and early child outcomes. *The Economic Journal, 126*(596), F96-F135.

Bradbury, K. & Triest, R. K. (2016). Introduction: Inequality of economic opportunity. *The Russell Sage Foundation Journal of the Social Sciences, 2,* 1-43.

Bradley, R. H., & Caldwell, B. M. (1979). Home Observation for Measurement of the Environment: A revision of the preschool scale. *American Journal of Mental Deficiency, 84*(3), 235-244.

Bradley, R. H., & Corwyn, R. F. (2004). Family process investments that matter for child well-being. In A. Kalil & T. DeLeire (Eds.), *Family investments in children's potential: Resources and parenting behaviors that promote success* (pp. 1-32). Abington-on-Thames, UK: Psychology Press Taylor & Francis Group.

Briggs, X. S. (1998). Brown kids in White suburbs: Housing mobility and the many faces of social capital. *Housing Policy Debate*, *9*, 177–221.

Bronfenbrenner, U. & Morris, P. (2006). The bioecological model of human development. In R. Lerner & W. Damon (Eds.), *Handbook of Child Psychology*, Vol. 1 (6th ed., pp. 793-828). Hoboken, NJ: John Wiley & Sons.

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

Cangur, S. & Ercan, I. (2015) Comparison of model fit indices used in structural equation modeling under multivariate normality. *Journal of Modern Applied Statistical Methods, 14*(1), 152-167.

Carpiano, R. M., Lloyd, J. E., & Hertzman, C. (2009). Concentrated affluence, concentrated disadvantage, and children's readiness for school: A population-based, multi-level investigation. *Social Science & Medicine, 69*(3), 420-432.

Casciano, R., and Massey, D.S. (2012). School context and educational outcomes: Results from a quasiexperimental study. *Urban Affairs Review, 48*, 180–204.

Chetty, R., Hendren, N., Jones, M. R., & Porter, S. R. (2020). Race and economic opportunity in the United States: An intergenerational perspective. *The Quarterly Journal of Economics,* 711–783. doi:10.1093/qje/qjz042

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

Coley, R. L., Kull, M., & Carrano, J. (2014). Parental spanking endorsement and children's internalizing and externalizing behaviors in African American and Hispanic families. *Journal of Family Psychology, 28*(1)*,* 22-31.

Coley, R. L., Lynch, A. D., & Kull, M. (2015). Early exposure to environmental chaos and children's physical and mental health. *Early Childhood Research Quarterly, 32*, 94-104.

Coley, R. L., Sims, J., Dearing, E., & Spielvogel, B. (2018). Locating economic risks for adolescent well-being: Poverty and affluence in families, schools, and neighborhoods. *Child Development, 89,* 360-369. *DOI: 10.1111/cdev.12771*

Coley, R. L., Spielvogel, B. & Sims, J. (2018). Are the benefits of economic resources for socioemotional functioning shared across racial and ethnic groups? *Journal of Youth and Adolescence*, 47, 2503–2520. https://doi.org/10.1007/s10964-018-0900-z

Coley, R. L., Votruba-Drzal, E., Collins, M. A., & Miller, P. (2014). Selection into early education and care settings: Differences by developmental period. *Early Childhood Research Quarterly*, *29*(3), 319-332.

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

Cuartas, J. (2018). Neighborhood crime undermines parenting: Violence in the vicinity of households as a predictor of aggressive discipline. *Child Abuse & Neglect, 76*, 388-399.

DeGangi, G., Poisson, S., Sickel, R., & Wiener, A. (1995). *Infant-Toddler Symptom Checklist: A screening tool for parents* [Measurement instrument]. Tuscon, AZ: Therapy Skill Builders.

Dreier, P., Mollenkopf, J. & Swanstrom, T. (2014). *Place matters.* University Press of Kansas.

Duncan, G. J., Magnuson, K., & Votruba-Drzal, E. (2017). Moving beyond correlations in assessing the consequences of poverty. *Annual Review of Psychology, 68*, 413-434.

Duncan, S. E., & De Avila, E. A. (1998). *PreLAS* [Measurement instrument]. Monterey, CA: CTB/McGraw-Hill.

Dunn, L. M., & Dunn, L. M. (1997). *PPVT III: Peabody Picture Vocabulary Test, Third Edition* [Measurement instrument]. Circle Pines, MN: American Guidance Service.

Dupéré, V., Leventhal, T., Crosnoe, R., and Dion, E. (2010). Understanding the positive role of neighborhood socioeconomic advantage in achievement: The contribution of the home, child care, and school environments. *Developmental Psychology, 46*(5), 1227–1244.

Evans, G. W., & Kim, P. (2013). Childhood poverty, chronic stress, self-regulation, and coping. *Child Development Perspectives, 7*(1), 43-48.

Fiorini, M., & Keane, M. P. (2014). How the allocation of children's time affects cognitive and noncognitive development. *Journal of Labor Economics, 32*(4), 787-836.

Firebaugh, G., & Farrell, C. R. (2016). Still large, but narrowing: The sizable decline in racial neighborhood inequality in metropolitan America, 1980–2010. *Demography*, *53*(1), 139–164. https://doi.org/10.1007/s13524-015-0447-5

Flouri, E., & Midouhas, E. (2017). Environmental adversity and children's early trajectories of problem behavior: The role of harsh parental discipline. *Journal of Family Psychology, 31*(2), 234.

Formoso, D., Weber, R. N., & Atkins, M. S. (2010). Gentrification and urban children's well-being: Tipping the scales from problems to promise. *American Journal of Community Psychology*, *46*(3-4), 395-412.

Fuller, B., Bridges, M., Bein, E., Jang, H., Jung, S., Rabe-Hesketh, S., ... & Kuo, A. (2009). The health and cognitive growth of Latino toddlers: at risk or immigrant paradox? *Maternal and Child Health Journal*, *13*(6), 755-768.

Gershoff, E. T., Aber, J. L., Raver, C. C., & Lennon, M. C. (2007). Income is not enough: Incorporating material hardship into models of income associations with parenting and child development. *Child Development, 78,* 70-95. doi: 10.1111/j.1467-8624.2007.00986.x

Gershoff, E. T. & Grogan-Kaylor, A. (2016). Spanking and child outcomes: Old controversies and new meta-analyses. *Journal of Family Psychology, 30*, 453-469.

Ginsburg, H., & Baroody, A. J. (2003). *TEMA-3: Test of Early Mathematics Ability.* Austin, TX: Pro-Ed.

Gordon, R. A., & Chase-Lansdale, P. L. (2001). Availability of child care in the United States: A description and analysis of data sources. *Demography, 38*(2), 299-316.

Hajat, A., Diez-Roux, A. V., Adar, S. D., Auchincloss, A. H., Lovasi, G. S., O'Neill, M. S., ... & Kaufman, J. D. (2013). Air pollution and individual and neighborhood socioeconomic status: evidence from the Multi-Ethnic Study of Atherosclerosis (MESA). *Environmental Health Perspectives, 121*(11-12), 1325-1333.

Henry, D. A., Betancur Cortés, L., & Votruba-Drzal, E. (2020). Black–White achievement gaps differ by family socioeconomic status from early childhood through early adolescence. *Journal of Educational Psychology.* Advance online publication. https://doi.org/10.1037/edu000043.9

Henry, D. A., Votruba-Drzal, E., & Miller, P. (2019). Child development at the intersection of race and SES: An overview. In Henry, D. A., Votruba-Drzal, E., & Miller, P. (Eds.), *Advances in child development and behavior* (pp. 1-25). Elsevier Inc. https://doiorg/10.1016/bs.acdb.2019.05.002

Herbers, J. E., Garcia, E. B., & Obradović, J. (2017). Parenting assessed by observation versus parent-report: Moderation by parent distress and family socioeconomic status. *Journal of Child and Family Studies, 26*, 3339-3350. https://doi.org/10.1007/s10826-017-0848-8

Honaker, J., King, G., & Blackwell, M. (2018). *Amelia II: A program for missing data.* Retrieved from: https://cran.r-project.org/web/packages/Amelia/vignettes/amelia.pdf

Hope, E. C., Hoggard, L. S., & Thomas, A. (2015). Emerging into adulthood in the face of racial discrimination: Physiological, psychological, and sociopolitical consequences for African American youth. *Translational Issues in Psychological Science, 1*(4), 342-351.

ICF International (2011). *An overview of methods for EPA's National-Scale Air Toxics Assessment*. Durham, North Carolina: Author.

Kalil, A., Ziol-Guest, K. M., Ryan, R. M., & Markowitz, A. J. (2016). Changes in income-based gaps in parent activities with young children from 1988 to 2012. *AERA Open, 2*(3), 1-17.

Kling, J. R., Liebman, J. B., & Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica*, *75*, 83–119.

Kochhar, R. & Cilluffo, A. (2018). *Income inequality in the U.S., is rising most rapidly among Asians.* Pew Research Center. https://www.pewsocialtrends.org/2018/07/12/income-inequality-in-the-u-s-is-rising-most-rapidly-among-asians/

Kohen, D. E., Leventhal, T., Dahinten, V. S., & McIntosh, C. N. (2008). Neighborhood disadvantage: Pathways of effects for young children. *Child Development, 79*(1), 156-169.

Kornrich, S., & Furstenberg, F. (2013). Investing in children: Changes in parental spending on children, 1972–2007. *Demography, 50*(1), 1-23.

Leventhal, T., & Brooks-Gunn, J. (2003). Moving to opportunity: An experimental study of neighborhood effects on mental health. *American Journal of Public Health, 93*, 1576-1582.

Leventhal, T., Dupéré, V., & A. Shuey, E. (2015). Children in neighborhoods. In R. M. Lerner, M. H. Bornstein & T. Leventhal (Eds.), *Handbook of Child Psychology and Developmental Science* (pp. 493-533). Hoboken, NJ: Wiley.

Linares, L. O., Heeren, T., Bronfman, E., Zuckerman, B., Augustyn, M., & Tronick, E. (2001). A mediational model for the impact of exposure to community violence on early child behavior problems. *Child Development, 72*(2), 639-652.

Lonigan, C. J., Wagner, R. K., Torgesen, J. K., & Rashotte, C. A. (2003). *Preschool Comprehensive Test of Phonological and Print Processing*. Austin, TX: Pro-Ed.

Lund, T. J., & Dearing, E. (2013). Is growing up affluent risky for adolescents or is the problem growing up in an affluent neighborhood? *Journal of Research on Adolescence*, *23*(2), 274-282. doi**:** 10.1111/j.1532-7795.2012.00829.x

Luthar, S. S., Barkin, S. H., & Crossman, E. J. (2013). "I can, therefore I must": Fragility in the upper-middle classes. *Development and Psychopathology*, *25*(402), 1529-1549. doi: 10.1017/S0954579413000758

MacKinnon, D. P. (2008). *Multivariate applications series. Introduction to statistical mediation analysis.* New York, NY: Taylor & Francis Group/Lawrence Erlbaum Associates.

Masarik, A. S., & Conger, R. D. (2017). Stress and child development: A review of the Family Stress Model. *Current Opinion in Psychology, 13*, 85-90.

McEwen, C. A., & McEwen, B. S. (2017). Social structure, adversity, toxic stress, and inter-generational poverty: An early childhood model. *Annual Review of Sociology, 43*, 445-472.

Michalopoulos, C., Faucetta, K., Hill, C. J., Portilla, X. A., Burrell, L., Lee, H., Duggan, A., & Knox V. (2019). *Impacts on family outcomes of evidence-based early childhood home visiting: Results from the Mother and Infant Home Visiting Program Evaluation*. OPRE Report 2019-07. Washington, DC: Office of Planning, Research, and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services.

Miller, P., Votruba-Drzal, E., & Coley, R. L. (2019). Poverty and academic achievement across the urban to rural landscape: Associations with community resources and stressors. *The Russell Sage Foundation Journal of the Social Sciences, 5*(2), 106-122.

Najarian, M., Snow, K., Lennon, J., and Kinsey, S. (2010). Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), preschool–kindergarten 2007 Ppsychometric Rreport (NCES 2010-009). National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

National Academy of Sciences, Engineering, and Medicine (2019). *A roadmap to reducing child poverty*. Washington DC: The National Academies Press.

National Center for Education Statistics (2000). *Bayley Short Form-Research Edition*. Washington DC: National Center for Education Statistics.

Odgers, C. L., Caspi, A., Russell, M. A., Sampson, R. J., Arseneault, L., & Moffitt, T. E. (2012). Supportive parenting mediates neighborhood socioeconomic disparities in children's antisocial behavior from ages 5 to 12. *Development and Psychopathology, 24*(3), 705-721.

Owens, A. (2018). Income segregation between school districts and inequality in students' achievement. *Sociology of Education, 91,* 1-27.

Owens, A. & Clampet-Lundquist, S. (2017). Housing mobility and the intergenerational durability of neighborhood poverty. *Journal of Urban Affairs, 39*, 400-420. DOI: 10.1080/07352166.2016.1245083

Owens, A., Reardon, S. F., & Jencks, C. (2016). Income segregation between schools and school districts. *American Educational Research Journal, 53*(4), 1159-1197.

Phillips, M. (2011). Parenting, time use, and disparities in academic outcomes. In G. J. Duncan & R. J. Murnane (Eds.), *Whither opportunity* (pp. 207–228). New York, NY: Russell Sage.

Price, J., & Kalil, A. (2018). The effect of mother-child reading time on children's reading skills: Evidence from natural within-family variation. *Child Development*, *90*(6), e688-e702.

Puma, M., Bell, S., Cook, R., Heid, C., Shapiro, G., Broene, P., ... & Ciarico, J. (2010). *Head Start Impact Study final report*. Washington DC: US Dept of Health and Human Services.

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

Reardon, S. F., & Bischoff, K. (2013). Residential segregation by income, 1970–2009. In J. Logan (Ed.), *Diversity and disparities: America enters a new century* (pp. 208-233). New York, NY: Russell Sage.

Reardon, S. F., Fox, L., & Townsend, J. (2015). Neighborhood income composition by household race and income, 1990–2009. *Annals of the American Academy of Political and Social Science*, *660*(1), 78–97. https://doi.org/10.1177/0002716215576104

Reardon, S. F., & Portilla, X. A. (2016). Recent trends in income, racial, and ethnic school readiness gaps at kindergarten entry. *AERA Open*, *2*(3), 1-18.

Roscigno, V. J., Karafin, D. L., & Tester, G. (2009). The complexities and processes of racial housing discrimination. *Social Problems*, *56*(1), 49–69. https://doi.org/10.1525/sp.2009.56.1.49

Rothstein, R. (2017). *The Color of Law: A Forgotten History of How Our Government Segregated America*. Liveright Publishing.

Rubin, D. B. (1987). *Multiple imputation for nonresponse in surveys*. New York: Wiley.

Sampson, R. J., Sharkey, P., & Raudenbush, S. W. (2008). Durable effects of concentrated disadvantage on verbal ability among African-American children. *Proceedings of the National Academy of Sciences, 105*(3), 845-852.

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

Sharkey, P. T. (2010). The acute effect of local homicides on children's cognitive performance. *Proceedings of the National Academy of Sciences, 107*(26), 11733-11738.

Sharkey, P. T., Tirado-Strayer, N., Papachristos, A. V., & Raver, C. C. (2012). The effect of local violence on children's attention and impulse control. *American Journal of Public Health, 102*(12), 2287-2293.

Shonkoff, J. P. (2010). Building a new biodevelopmental framework to guide the future of early childhood policy. *Child Development, 81*(1), 357-367.

Shonkoff, J. P. (2012). Leveraging the biology of adversity to address the roots of disparities in health and development. *Proceedings of the National Academy of Sciences, 109*(Supplement 2), 17302-17307.

Shuey, E. A., and Leventhal, T. (2017). Pathways of risk and resilience between neighborhood socioeconomic conditions and child maltreatment. *Children and Youth Services Review, 72*, 52-59. https://doi. org/10.1016/j.childyouth.2016.09.031

Small, M. L. (2006). Neighborhood institutions as resource brokers: Childcare centers, inter-organizational ties, and resource access among the poor. *Social Problems, 53*(2), 274-292.

Stone, L. L., Otten, R., Engels, R., Vermulst, A. A., & and Janssens, J. (2010). Psychometric properties of the parent and teacher versions of the Strengths and Difficulties Questionnaire for 4- to 12-year-olds: A review. *Clinical Child Family Psychology Review, 13(3)*, 254–274. doi: 10.1007/s10567-010-0071-2

Stucky, T. D., Payton, S. B., & Ottensmann, J. R. (2016). Intra-and inter-neighborhood income inequality and crime. *Journal of Crime and Justice, 39*(3), 345-362.

Turner, M. A. (2008). Limits on housing and neighborhood choice: Discrimination and segregation in U.S. housing markets. *Indiana Law Review*, *41*(3), 797–816.

U.S. Census Bureau. (2018). Real median household income by race and Hispanic origin: 1967 to 2017 [Figure]. Current Population Survey, 1968 to 2018 Annual Social and Economic Supplements. https://www.census.gov/content/dam/Census/library/visualizations/2018/demo/p60-263/figure1.pdf

Vernon-Feagans, L., Cox, M., Willoughby, M., Burchinal, M., Garrett-Peters, P., Mills-Koonce, R., ... & Bauer, P. J. (2013). The Family Life Project: An epidemiological and developmental study of young children living in poor rural communities. *Monographs of the Society for Research in Child Development*, *78*(5), 1-150.

Votruba-Drzal, E., Miller, P., Coley, R. L., & Spielvogel, B. (2018). *Using national survey data, administrative data, and GIS to determine community boundaries across cities, suburbs, and rural areas.* Conference paper. Washington, D.C.: Society for Research in Child Development.

Wilhelm, M., Qian, L., & Ritz, B. (2009). Outdoor air pollution, family and neighborhood environment, and asthma in LA FANS children. *Health & Place, 15*(1), 25-36.

Xie, Y. (2011). Causal inference and heterogeneity bias in social science. Information *Knowledge Systems Management, 10*, 279-289. doi: 10.3233/IKS-2012-0197

Yeung, W. J., Linver, M. R., & Brooks–Gunn, J. (2002). How money matters for young children's development: Parental investment and family processes. *Child Development, 73*(6), 1861-1879.

Zaslow, M. J., Weinfield, N. S., Gallagher, M., Hair, E. C., Ogawa, J. R., Egeland, B., ... & De Temple, J. M. (2006). Longitudinal prediction of child outcomes from differing measures of parenting in a low-income sample. *Developmental psychology*, *42*(1), 27-37.

Table 1. Family, Community, and Child Measures

Measure	Operationalization	Source	Geography
Family Income	Parent report of total household income in prior year. Waves 1-3, averaged.	ECLS-B	-
Cultural Resources	Number of performing arts companies; museums, historical sites, zoos, botanical gardens, and nature parks; other amusement and recreational industries, including golf courses, skiing facilities, marinas, fitness and recreational sports centers, bowling centers; and sports and recreation instruction. Waves 2-4, averaged.	Economic Census	Within home zip code
Educational Resources	Number of elementary and secondary schools; child day care services; and educational support services, including career and vocational counseling, college selection services, study abroad programs, testing services, and other services that support educational processes or systems. Waves 2-4, averaged.	Economic Census	Within 10 miles of home zip code
Concentrated Socioeconomic Disadvantage	The proportion of residents who lived under the poverty line, received public assistance, were unemployed, had not completed high school, or lived in female-headed households, standardized and averaged. Waves 2-4, averaged.	2000 Decennial Census	Within home zip code
Crime	Average monthly violent crime rate (per 10,000 people), including assault, homicide, and sexual assault. Waves 2-4, averaged.	FBI Uniform Crime Reporting Database	Within 2 miles of home zip code
Community Air Pollution	Concentration of air-born chemicals associated with adverse effects on the central nervous system. Waves 2-4, averaged.	EPA National Air Toxics Assessment	Within home zip code
Cognitive Stimulation	Parent-reported child engagement in activities such as reading books, singing, taking trips to zoos and libraries. Waves 2-4, averaged.	ECLS-B	-
Emotional Support	Direct assessment of parents' sensitivity to and positive regard for child during semi-structured play activities. Waves 2-3, averaged.	ECLS-B	-
Harsh Discipline	Parent-reported use of spanking and hitting as discipline strategies, and whether had spanked child in the past week, summed. Waves 2-4, averaged.	ECLS-B	-
Child Cognitive Skills	Direct assessment of children's reading and math skills, standardized and averaged. Wave 4.	ECLS-B	-
Child Externalizing Behaviors	Teacher reports of children's externalizing behaviors such as aggression and temper tantrums. Wave 4.	ECLS-B	-
Covariates	Parent reports of child, parent, and family characteristics. Waves 1-4, averaged.	ECLS-B	-

Note. Table delineates data for the primary analyses. Additional model specifications used different combinations of data across waves.

Table 2: Weighted Sample Descriptives

	Mean	SD	Missing		Proportion	Missing
Child outcomes				Child & family covariates, cont		
Externalizing problems W4	1.93	0.8	52%	Child sex: Female W1	48.90%	0%
Cognitive skills W4	-0.02	0.95	22-36%	Child sex: Male W1	51.10%	0%
Family income ($10,000) W1-3	5.78	4.67	0-16%	Child race: White W1	53.39%	0%
Community processes				Child race: Black W1	13.69%	0%
Educational resources W2-4	478.73	616.85	10-36%	Child race: Hispanic W1	25.49%	0%
Cultural resources W2-4	6.11	4.57	22-44%	Child race: Asian, Hawaiian, or PI W1	2.98%	0%
Concentrated disadvantage W2-4	-0.04	0.97	9-36%	Child race: American Indian W1	0.50%	0%
Violent crime (per 10,000) W2-4	9.62	7.37	41-57%	Child race: Multiracial W1	3.96%	0%
Air pollution W2-4	0.06	0.05	13-38%	Low birth weight W1	7.45%	1%
Family processes				Language: Non-English across waves W1-3	17.97%	0-35%
Cognitive stimulation W2-4	0.05	1.02	8-34%	Language: Non-English some waves W1-3	2.99%	0-35%
Emotional support W2-3	4.52	0.73	28-29%	Language: English across waves W1-3	79.03%	0-35%
Harsh discipline W2-4	0.85	0.77	8-35%	Immigrant parent W1	24.15%	5%
Child & family covariates				Mother married across waves W1-3	63.66%	0-36%
Child age W4	5.39	0.31	34%	Mother single across waves W1-3	22.99%	0-36%
Temperament W1	0.05	0.43	4%	Mother change in status W1-3	13.35%	0-36%
Cognitive skills W1	76.7	9.73	5%	Parent education: Below high school W1-3	9.79%	1-34%
Months in kindergarten W4	2.17	1.9	35%	Parent education: High school W1-3	23.43%	1-34%
Number of kids in HH W1-3	2.3	1.05	8-34%	Parent education: Some college W1-3	30.29%	1-34%
Mother age W1	33.16	6.64	1%	Parent education: Bachelor's degree W1-3	21.36%	1-34%
Res mobility (# moves) W1-3	1.48	1.79	8-34%	Parent education: Graduate degree W1-3	15.13%	1-34%
				Region: Northeast W1-3	16.42%	0-34%
				Region: Midwest W1-3	22.78%	0-34%
				Region: South W1-3	37.57%	0-34%
				Region: West W1-3	23.23%	0-34%

Note: Table displays weighted pre-imputation descriptives. Data derived from the restricted use ECLS-B data waves 1 – 4 provided by the National Center for Education Statistics, U.S. Department of Education.

Table 3: SEM Model Results Linking Family Income to Children's Functioning

	Cognitive Skills	Externalizing Problems
Direct Paths	β (SE)	β (SE)
income → educational resources	0.252 (0.018)**	0.252 (0.018)**
income → cultural resources	0.199 (0.022)**	0.199 (0.022)**
income → concentrated disadvantage	-0.335 (0.017)**	-0.335 (0.017)**
income → violent crime rate	-0.096 (0.024)**	-0.096 (0.024)**
income → air pollution	0.034 (0.02)	0.034 (0.02)
educational resources→ cognitive stimulation	0.046 (0.014)**	0.046 (0.014)**
cultural resources → cognitive stimulation	0.042 (0.014)**	0.042 (0.014)**
concentrated disadvantage → cognitive stimulation	-0.055 (0.017)**	-0.055 (0.017)**
violent crime rate → cognitive stimulation	-	-
air pollution → cognitive stimulation	-	-
income → cognitive stimulation	0.097 (0.019)**	0.097 (0.019)**
educational resources → emotional support	-	-
cultural resources → emotional support	0.036 (0.015)*	0.036 (0.015)*
concentrated disadvantage → emotional support	-0.069 (0.019)**	-0.069 (0.019)**
violent crime rate → emotional support	-	-
air pollution → emotional support	-	-
income → emotional support	0.114 (0.02)**	0.114 (0.02)**
educational resources→ harsh discipline	-0.083 (0.016)**	-0.083 (0.016)**
cultural resources → harsh discipline	-0.035 (0.014)*	-0.036 (0.014)*
concentrated disadvantage → harsh discipline	0.058 (0.018)**	0.058 (0.018)**
violent crime rate → harsh discipline	0.041 (0.015)**	0.042 (0.015)**
air pollution → harsh discipline	-	-
income → harsh discipline	-0.067 (0.02)**	-0.067 (0.02)**
cognitive stimulation → child functioning	0.157 (0.015)**	-0.103 (0.021)**
emotional support → child functioning	0.067 (0.015)**	-
harsh discipline → child functioning	-	0.077 (0.018)**
educational resources→ child functioning	0.038 (0.017)*	-
cultural resources → child functioning	-	-
concentrated disadvantage → child functioning	-	-0.039 (0.02)*
violent crime rate → child functioning	-	-
air pollution → child functioning	-0.036 (0.016)*	-
income → child functioning	0.132 (0.018)**	-

Note: ** $p < 0.01$; * $p < 0.05$. Standardized coefficients and SEs presented. Paths from covariates (child age, race, gender, low birth weight, months in kindergarten, temperament, and cognitive skills in infancy, as well as household size, language spoken at home, immigrant status, parent age, education, and marital status, residential mobility, and region) to family income, community measures, parenting measures, and child outcomes not shown. Data derived from the restricted use ECLS-B data waves 1 – 4 provided by the National Center for Education Statistics, U.S. Department of Education.

Table 4: SEM Model Indirect, Direct, and Total Effects

	Cognitive Skills	Externalizing Problems
Indirect Effects	β (SE)	β (SE)
income → child functioning		
VIA educational resources	0.010 (0.004)*	-
VIA cultural resources	-	-
VIA concentrated disadvantage	-	-
VIA violent crime	-	-
VIA air pollution	-0.001 (0.001)	-
VIA educational resources→ cognitive stimulation	0.002 (0.001)**	-0.001 (0)**
VIA cultural resources → cognitive stimulation	0.001 (0.000)**	-0.001 (0)*
VIA concentrated disadvantage → cognitive stimulation	0.003 (0.001)**	-0.002 (0.001)**
VIA violent crime → cognitive stimulation	-	-
VIA air pollution → cognitive stimulation	-	-
VIA cognitive stimulation	0.015 (0.003)**	-0.010 (0.003)**
VIA educational resources→ emotional support	-	-
VIA cultural resources → emotional support	0.000 (0.000)*	-
VIA concentrated disadvantage → emotional support	0.002 (0.001)**	-
VIA violent crime → emotional support	-	-
VIA air pollution → emotional support	-	-
VIA emotional support	0.008 (0.002)**	-
VIA educational resources→ harsh discipline	-	-0.002 (0.00)**
VIA cultural resources → harsh discipline	-	-0.001 (0.00)*
VIA concentrated disadvantage → harsh discipline	-	-0.001 (0.001)*
VIA violent crime → harsh discipline	-	0.00 (0.00)*
VIA air pollution → harsh discipline	-	-
VIA harsh discipline	-	-0.005 (0.002)**
Total indirect effect	0.039 (0.006)**	-0.010 (0.008)
Direct Effect		
income → child functioning	0.132 (0.018)**	-
Total Effect (indirect + direct)	0.172 (0.018)**	-0.010 (0.008)

Note: ** $p < 0.01$; * $p < 0.05$. Standardized coefficients and SEs presented. Paths from covariates (child age, race, gender, low birth weight, months in kindergarten, temperament, and cognitive skills in infancy, as well as household size, language spoken at home, immigrant status, parent age, education, and marital status, residential mobility, and region) to family income, community measures, parenting measures, and child outcomes not shown. Data derived from the restricted use ECLS-B data waves 1 – 4 provided by the National Center for Education Statistics, U.S. Department of Education.

Figure 1: Conceptual Model

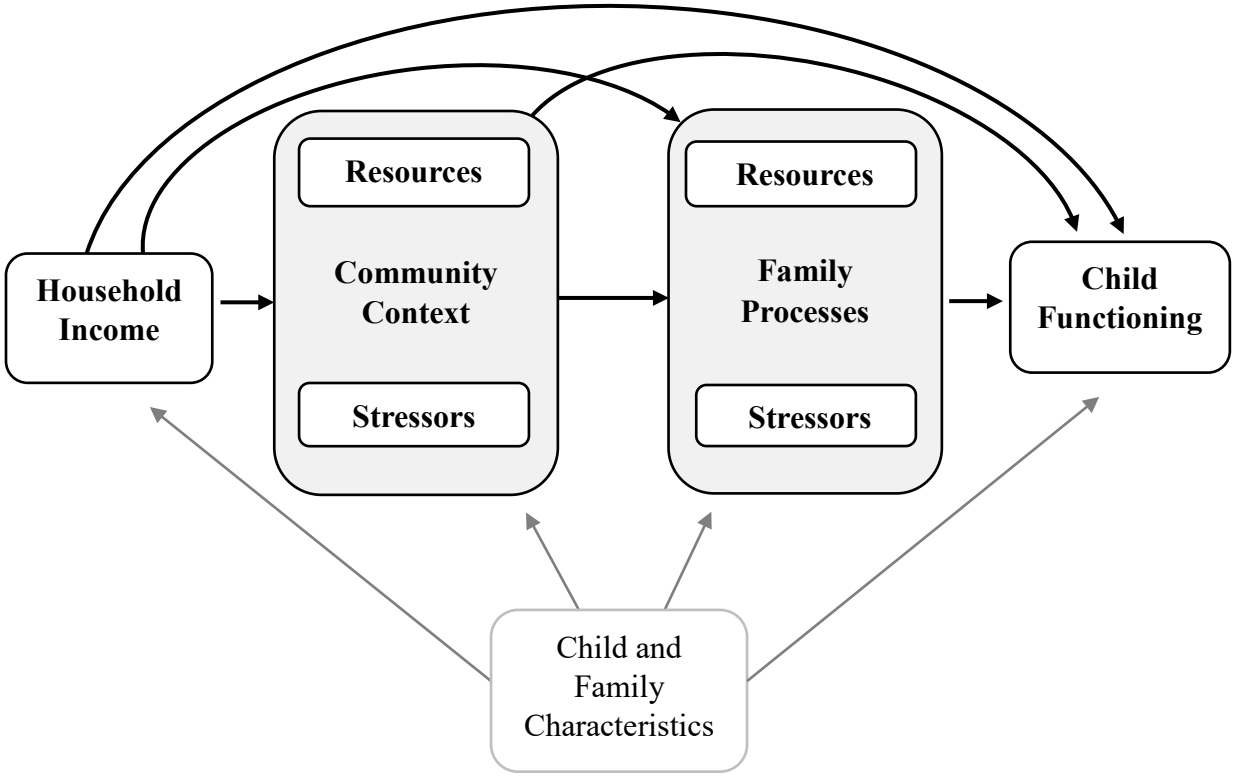
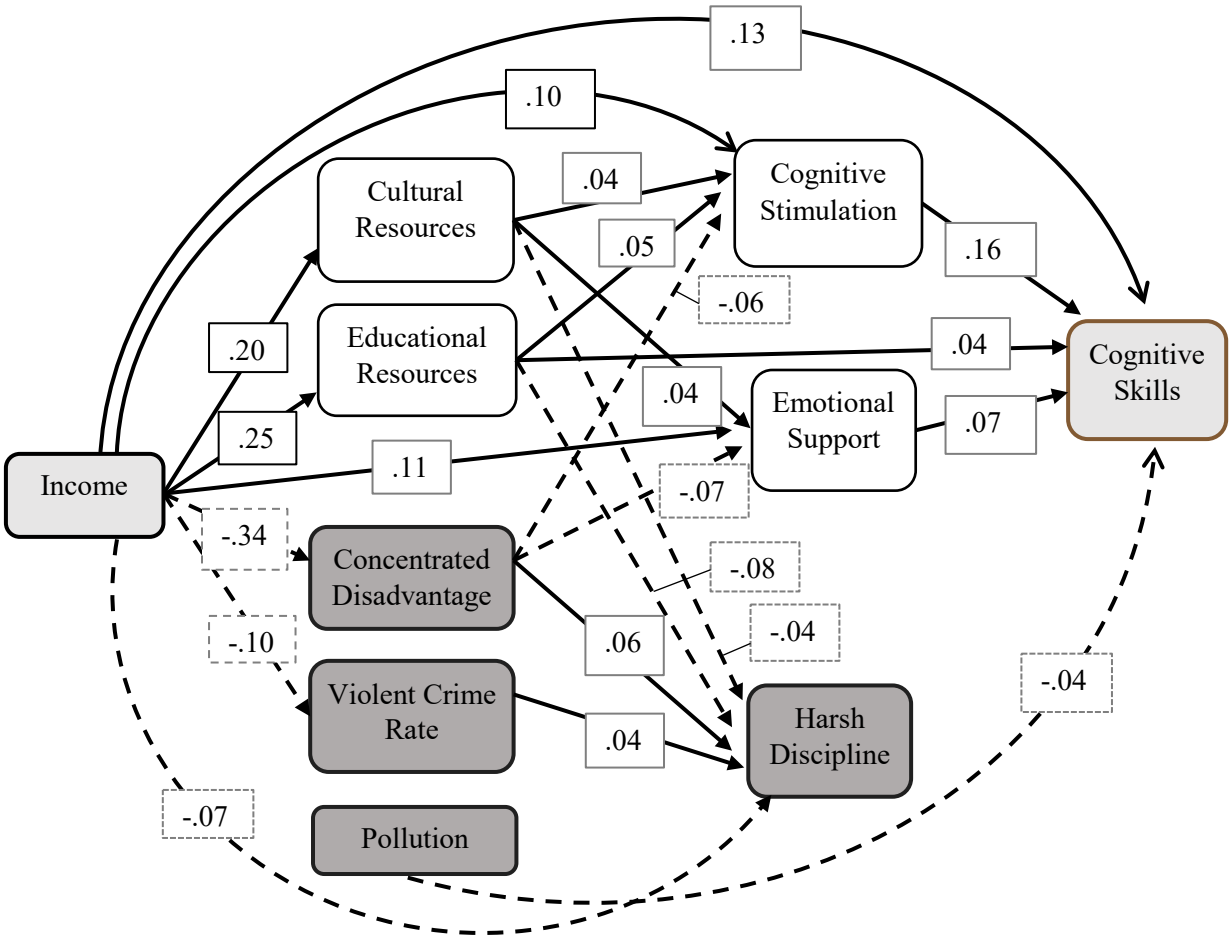
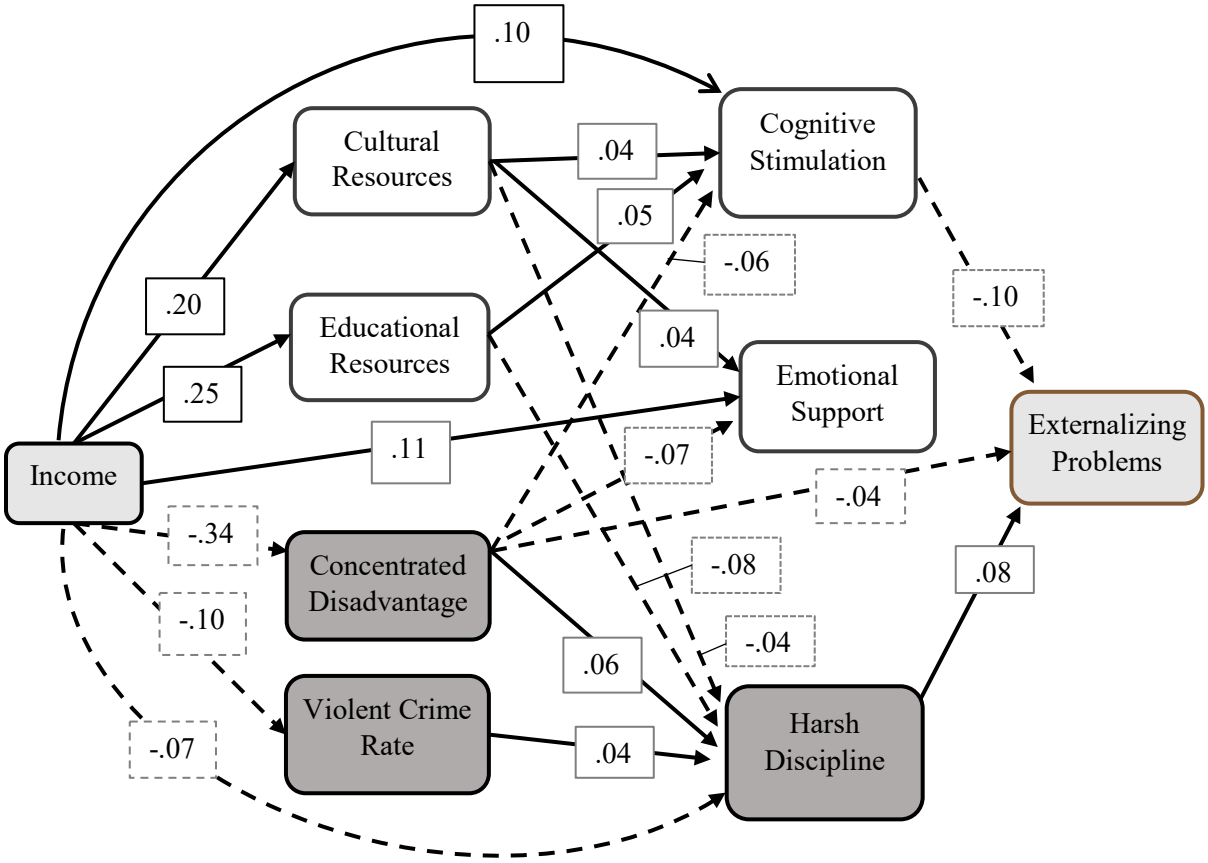


Figure 2: Significant Direct and Indirect Paths Linking Family Income to Children's Cognitive Skills



Note: Only paths significant at p<.05 are pictured. Standardized coefficients are presented for each path. Solid lines indicate positive associations; dashed lines indicate negative associations. Constructs shown in dark grey represent stressors; those shown in white constitute resources. Standard errors are clustered at zip code level, and models control for child age, race, gender, low birth weight, months in kindergarten, temperament, and cognitive skills in infancy, as well as household size, language spoken at home, immigrant status, parent age, education, and marital status, residential mobility, and region.

Figure 3: Significant Direct and Indirect Paths Linking Family Income to Children's Externalizing Problems



Note: Only paths significant at p<.05 are pictured. Standardized coefficients are presented for each path. Solid lines indicate positive associations; dashed lines indicate negative associations. Constructs shown in dark grey represent stressors; those shown in white constitute resources. Standard errors are clustered at zip code level, and models control for child age, race, gender, low birth weight, months in kindergarten, temperament, and cognitive skills in infancy, as well as household size, language spoken at home, immigrant status, parent age, education, and marital status, residential mobility, and region.