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Neighborhood Contexts and Child Maltreatment Reports Among Families Receiving AFDC/TANF: A Longitudinal and Multilevel Study

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Abstract

Attention to the relationship between neighborhood context and child maltreatment is growing. However, no study exists that considers families' residential moves and neighborhood changes longitudinally. This is particularly relevant to disadvantaged families who move frequently. Our sample includes children who experienced a child maltreatment report (CMR) or an AFDC case in early childhood. We followed up these children from 1995 to 2009 through various administrative databases. We used multilevel logistic growth curve models to estimate the CMR likelihood at each age from 1 to 16. Estimates were limited to ages on AFDC/TANF to trace families' residential addresses based on AFDC/TANF payee records. Our findings highlight the importance of tracing residential neighborhoods in a longitudinal study. While doing so, we identify some possible neighborhood contextual influences. These, however, are small in contribution to overall risk and are less observable among children that are more vulnerable.

Introduction

There is a longstanding recognition of the importance of neighborhood ecology in understanding child maltreatment (Garbarino, 1977). Some research using sophisticated methodologies, such as multilevel modeling, to examine neighborhood contextual effects began to emerge around the turn of the century (Coulton, Korbin, & Su, 1999; Freisthler & Maguire-Jack, 2015; Freisthler & Wolf, 2016; Irwin, 2009; Kim & Drake, 2017; Kim, 2004; Merritt, 2009; Molnar, Buka, Brennan, Holton, & Earls, 2003). These and other studies have tested neighborhood contextual effects in a cross-sectional manner or used baseline information while disregarding any change of residence over time. This is mainly due to the limited availability of longitudinal data showing changes in families' addresses. This study presents approaches and findings that can help to close gaps in the existing evidence base, notwithstanding unavoidable methodological and data limitations.

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Human Participant Protection: The current study's data were obtained from a larger longitudinal study which linked data from various Missouri administrative systems and Census data. The parent study is permitted to use these data with human subjects' approval by all service system agencies and the Washington University Hilltop Institutional Review Board. All personal identifiers (e.g., names) were already removed prior to accessing the data for the present study.

Prior Literature for Neighborhood Contextual Effects

Many neighborhood-level studies have found strong associations between neighborhood characteristics (e.g., poverty rates) and neighborhood child maltreatment rates (Coulton et al., 2007; Drake & Pandey, 1996; Freisthler et al., 2006). However, with such aggregate level findings, one cannot determine whether child maltreatment risks are associated with family characteristics (e.g., living in poverty) or with neighborhood contexts (e.g., living in a deprived neighborhood). A number of studies have attempted to address this issue by using multilevel modeling that considers both individual and neighborhood levels to examine the unique contributions of each. These multilevel studies have identified several important neighborhood characteristics that may have unique contributions to an individual's risk of child maltreatment.

Impoverishment.—High percentages of poverty, unemployment, vacant housing, concentrated minority populations, and female-headed families characterize impoverished neighborhoods. The sociological perspective suggests that neighborhood impoverishment may impede collective engagement for community children due to isolation of residents from adequate resources, high levels of distrust, fear of strangers, uncertainty, economic dependency, isolation of parents from employment opportunities and high levels of allostatic load within family members (Clampet-Lundquist & Massey, 2008; Sampson et al., 1999). From a psychological perspective, concentrated disadvantages may increase stress on families, which in turn may increase risk of child maltreatment (Belsky, 1980, 1993; Cicchetti & Lynch, 1993; Coulton et al., 2007; National Research Council, 2014; Pelton, 2015). From an economic perspective, it is possible that neighborhood impoverishment increases risk of child maltreatment simply by limiting available resources (e.g., high-quality daycare) to residents.

Prior multilevel findings were inconsistent. Irwin (2009) found that neighborhood impoverishment had a significant positive association with the likelihood of having an official maltreatment report. Coulton et al. (1999) and Merritt (2009) found that a higher level of neighborhood impoverishment was significantly associated with a higher self-reported score of physical abuse and neglect. Other studies found no significant associations for self-reported maltreatment and officially reported maltreatment (Freisthler & Maguire-Jack, 2015; Freisthler & Wolf, 2016; Kim & Drake, 2017; Kim, 2004; Molnar et al., 2003).

Instability.—High neighborhood instability suggests a high rate of residential moves and a low proportion of tenured residents. Frequent moves and resultant weakened social ties may hinder a community's collective engagement for child well-being (Sampson et al., 1999). Social ties are also important from the psychological perspective, as strong social ties can buffer environmental stressors (Belsky, 1980; Cicchetti & Lynch, 1993).

Prior multilevel findings on neighborhood instability were inconsistent. Freisthler and Maguire-Jack (2015) and Freisthler and Wolf (2016) found that a higher level of neighborhood instability was significantly associated with higher self-reported scores of physical abuse and neglect. Irwin (2009) also found a significant association between a higher level of residential instability and a higher likelihood of maltreatment reporting.

Other studies exploring self-reported maltreatment showed no significant finding for neighborhood instability (Coulton et al., 1999; Kim, 2004; Merritt, 2009; Molnar et al., 2003).

Child care burden.—Neighborhoods with proportionally more children and fewer female adults may have a higher child care burden because of insufficient numbers of adults being available to help with childrearing. The lack of child care resources to share with neighbors may reduce community collective engagement (Sampson et al., 1999) or heighten childrearing stress among residents (Belsky, 1980; Cicchetti & Lynch, 1993; Garbarino & Sherman, 1980).

The findings of prior multilevel studies regarding child care burden have not been consistent. Coulton et al. (1999) and Merritt (2009) found a significant positive association of neighborhood child care burden with self-reported physical abuse and neglect scores. However, other studies found no significant association of neighborhood child care burden with official maltreatment reports (Irwin, 2009) or with self-reported physical abuse acts (Freisthler & Wolf, 2016).

Ethnic Heterogeneity.—A higher level of naturalized Asian/Pacific Islanders in a neighborhood has been associated with an increased frequency of self-reported physical abuse acts (Freisthler & Maguire-Jack, 2015). Conversely, neighborhood immigrant concentration showed negative associations by significantly lowering self-reported physical abuse acts (Freisthler & Maguire-Jack, 2015) and self-reported parent-to-child physical aggression scores (Molnar et al., 2003). These negative associations go against a sociological perspective, which posits that immigrant concentration may obstruct collective engagement due to linguistic and cultural segregation (Sampson et al., 1999). Rather, these findings are consistent with an individual-level effect, the so-called “healthy immigrant effect” or decay of such an effect due to acculturation found both in the medical and the child welfare literature (Putnam-Hornstein et al., 2013). Kim (2004) found no significant association between neighborhood ethnic heterogeneity and surveyed maltreatment.

Alcohol and drug density.—A higher density of alcohol and drug availability or activities in a community can impair social ties and support for parenting practices. Regarding alcohol, Freisthler and colleagues found no significant association between alcohol outlet density and self-reported physical abuse (Freisthler & Maguire-Jack, 2015; Freisthler & Wolf, 2016). For drugs, however, Freisthler, Wolf, Wiegmann, and Kepple (2017) found that city-level rates of drug activities were associated with increased risk of self-reported child maltreatment.

Neighborhood process.—Neighborhood structures (e.g., impoverishment, instability, and child care burden) may influence neighborhood processes, such as social disorganization (i.e., a community’s structural inability for collective engagement) and collective efficacy (i.e., a community’s social cohesion for collective engagement) (Sampson et al., 1997, 1999; Sampson & Groves, 1989). Some studies found these neighborhood processes were significantly related to self-reported maltreatment (Freisthler & Maguire-Jack, 2015; Kim, 2004), while others did not (Coulton et al., 1999; Merritt, 2009).

In summary, despite strong theoretical support for neighborhood contextual effects, prior multilevel findings were inconsistent. It may be that underlying relationships among variables are complex, perhaps manifesting in interaction or synergistic effects. This inconsistency suggests that we need to accumulate more evidence to better understand any unique impacts of neighborhood contexts independent from individual characteristics. It is also important to consider changes of residential neighborhoods over time in a longitudinal setting as children, especially disadvantaged ones, move frequently (Coulton et al., 2012). There is only one prior study which examined the relationships between neighborhood contexts and maltreatment *reports* (Irwin, 2009). Although that study was longitudinal in nature, it limited the measures of neighborhood contexts at the baseline and disregarded their changes over time.

To address these gaps in knowledge, this study examines the associations between neighborhood contexts and children's risk of having a child maltreatment report (CMR). To assess *unique* neighborhood contexts independent from child/family characteristics, we used a multilevel model. To investigate *current* neighborhood contexts, we used for the first time a longitudinal model that considered children's changes of residential address over time. This allowed for considering changes of neighborhood contexts and family-level residential mobility simultaneously, while establishing temporal precedence of neighborhood contexts in relation to CMRs. Overall, this study examined the following three neighborhood characteristics in their associations with CMR likelihoods: impoverishment (poverty rate), instability (mobility rate), and child care burden (child/adult ratio). We further examined any difference in these associations by race as existing evidence suggests that the experience of neighborhood contexts may differ by race (Irwin, 2009). Finally, this study examined two important variables regarding residential mobility: residential moves and long-distance moves. Although these variables are closely related to changes of neighborhood contexts, evidence on these variables is sparse.

Methods

This study obtained data from a parent study (Jonson-Reid et al., 2009) that included high-risk children who resided in St. Louis (City and County) of Missouri in 1993-1994. The parent study had longitudinally traced these children within various Missouri statewide administrative databases through March 2009. From the parent study's data, we constructed longitudinal and multilevel data consisting of multiple age-year observations within children and neighborhoods. Multilevel logistic growth curve models estimated the CMR likelihood at each age (i.e., age-year observation) from 1 to 16 years as a function of a range of observation-level, child/family-level, and neighborhood-level predictors. Models further considered changes of predictors due to children's residential moves. To trace residential moves longitudinally, we used payee address in welfare records (Aid to Families with Dependent Children [AFDC] by 1997 and Temporary Assistance for Needy Families [TANF] after 1997). For this, we selected *only* age-year observations with an active AFDC/TANF cases. This selection limited estimates to age-year observations while receiving AFDC/TANF. However, this selection allowed for (1) assessment of current neighborhood contexts while establishing temporal precedence, (2) examining residential moves and long-distance moves, and (3) controlling family-level economic conditions. We discuss in the conclusion how this set of sampling limitations impacts the interpretation of our findings.

We estimated the likelihood of having any CMR (i.e., first, second, or any subsequent CMR) at a given age. We followed up children even after the first event and continued looking at the CMR likelihood at each of next ages in analyses. The strength of this approach is that we can estimate a model based on updated and time-specific neighborhood contexts. Methodologically, the possible difference in the CMR likelihood by the order of CMR at risk (i.e., the first CMR, the second CMR, …) was accounted by controlling for the number of prior CMRs in analyses.

Sampling and Follow-up

The parent study's data (Jonson-Reid et al., 2009) allowed our study to construct two separate samples. *The CAN (child abuse and neglect) sample* included all children from CPS records, who met the following criteria during the sampling period in 1993-1994: (1) having a first-time CMR for alleged neglect, physical abuse, or sexual abuse; (2) aged 3 years or younger; and (3) residing in St. Louis City or County. *The AFDC sample* included children randomly selected from AFDC records, who satisfied the following criteria during the sampling period (1993-1994): (1) having an active AFDC case; (2) having no CMR during the period; (3) aged 3 years or younger; and (4) residing in St. Louis City or County. For both samples, the parent study randomly selected one child per family when multiple children presented in a family. This made the child level equivalent to the family level in our study. For both samples, children were excluded if they or any sibling had any maltreatment report in the prior 3 years, or any substantiated maltreatment report or foster care event in the prior ten years.

The *CAN* and *AFDC* samples are not conceived of as comparison groups in a quasi-experimental design. Rather, these two groups allow for the research questions to be answered for different populations: (1) children who experienced a CMR in early childhood (*CAN*) and (2) children who had an AFDC case but no CMR in early childhood (*AFDC*). This was equivalent to the replication of a single study on different populations and extends generalizability.

We conducted analysis separately for each sample as accumulating evidence suggests that families can fundamentally differ by early childhood experience due to the lasting effects of early maltreatment or relevant risk and protective factors (Jonson-Reid et al., 2009; National Research Council, 2014). Methodologically, we did not merge two samples into one due to the lack of weighting information for the AFDC sample (i.e., a random sample of AFDC records) in comparison with the CAN sample (i.e., a full population of CAN records).

It is worth noting that we use the term "AFDC" to describe both the sample and welfare program. Whenever "AFDC" indicates a sample, we use the term with "sample" (i.e., "AFDC sample"). Otherwise, the term indicates the welfare program per se.

This study longitudinally traced the CAN and AFDC samples within the parent study's data. We followed up sampled children after the sampling period. The beginning age of follow-up varied from 1 to 4 years upon children's age at the time of sampling (i.e., 0 to 3 years). We finished our follow-up at the end of the parent study's data coverage (i.e., March 2009).

From all age-year observations of both samples during the follow-up period, we selected age-year observations with an active AFDC/TANF case to trace children's residential moves based on AFDC/TANF records. A child might leave AFDC/TANF at a certain age and never return to AFDC/TANF. Age-year observations of this child beyond that point were excluded and not considered for analyses. Some children might occasionally receive AFDC/TANF during follow-up, while other children might be continuously on AFDC/TANF over time. By selecting age-year observations on AFDC/TANF, both groups of children would have a low level of current family economic conditions at a given age in the study. The difference in cumulative history of AFDC/TANF receipt between these groups of children was considered in analyses by controlling for the percentage of months on AFDC/TANF since child's birth.

Before selecting age-year observations on AFDC/TANF, there were 32,348 (child-year) observations for the CAN sample and 25,596 observations for the AFDC sample. For data integrity, we excluded observations after the following events of the subject child: (1) death (< 1% of observations), (2) out-of-home placement (21.25% of CAN-sample and 3.70% of AFDC-sample observations), and (3) childbirth (< 0.01% of observations). Then, we selected observations with an active AFDC/TANF case. After this, there were 8,814 observations for the CAN sample and 7,393 observations for the AFDC sample. Some observations were further excluded for data integrity. First, we excluded observations after a change of the subject child's AFDC/TANF payee (10.62% of CAN-sample and 6.97% of AFDC-sample observations). This was because we could follow up only caregivers at the time of sampling for confidentiality protections. Second, we excluded observations with last known residential areas out of Missouri (0.01% of CAN-sample and 0.06% of AFDC-sample observations). This was because the study data could follow up only those residing within Missouri. Finally, we excluded observations with missing address information (1.09% of CAN-sample and none of AFDC-sample observations). The final samples covered child age from 1 to 16 years for both samples, specifically 7,881 age-year observations in 1,530 children and 385 neighborhoods for the CAN sample and 6,907 age-year observations in 1,436 children and 328 neighborhoods for the AFDC sample. We operationalized neighborhoods as census tracts. The parent study had geocoded addresses and linked them with tract-level census data (e.g., poverty rate) while suppressing original census tract numbers to protect confidentiality.

Data Structure

This study constructed longitudinal and multilevel data at the observation level, the child/family level, and the neighborhood level. While observations were nested in children and neighborhoods, the child and neighborhood levels were cross-classified rather than nested. This was because in our data, a child can have multiple neighborhoods. Fortunately, both completely nested structures and cross-classified structures are usable in mixed-effects models, and there is no difference in computational methods for these types (Bates, 2010).

Measures

Table 1 reports the study variables, their measures, and data sources. We measured all variables by longitudinally tracing children and their caregivers within administrative records for various service systems. We could establish temporal precedence of predictors in their relation to CMRs by using dates of service system contacts. It was possible, however, that the onset of a given problem (e.g., child injury) might precede the date of a service system contact (e.g., emergency room visit) occasionally. Since most administrative records were statewide, we could trace children moving out of St. Louis but only within Missouri. It was also possible to exclude age-year observations after the child moved out of Missouri (≤ 0.06%), when indicated in the AFDC/TANF case. Although special education and juvenile court records were less complete for Missouri outside St. Louis, children generally stayed in St. Louis during the follow-up period (92.9% of the CAN sample observations and 94.6% of the AFDC sample observations).

Child maltreatment report (CMR).—The outcome was a binary measure (yes/no) of having a CMR at a given age. We included both substantiated and unsubstantiated CMRs as empirical evidence suggests no practical difference by substantiation status with respect to a variety of future negative child outcomes (Drake et al., 2003; Hussey et al., 2005; Kohl et al., 2009; Leiter et al., 1994). Screened out reports were not available.

Family residential moves.—This measured the number of family residential moves at a given age using AFDC/TANF records. Within each year children made 0 to 4 moves. As a few children made more than 2 moves, this variable was categorized as “0”, “1”, and “2 or more”.

Child race.—This variable measured the subject child’s race/ethnicity: Non-Hispanic White, Non-Hispanic Black and Other (including Asian, Hispanic/Latino, and other groups). The population of the study site (St. Louis City and County) was 74% White, followed by Black (23%), Asian (1%), Hispanic/Latino (1%), and other minority (<1%).

Neighborhood factors.—We used Census community variables from the Census 1990 and 2000 and the American Community Survey 2005-2009 and 2006-2010. Selection of specific variables follows the lead of Irwin (2009), with eleven neighborhood indicators utilized in our principal component analysis. We identified the following three factors: *impoverishment, instability*, and *child care burden*. The Supplement (the Neighborhood Factors section and Tables S1–S2) reports the measurement methods and results.

Neighborhood variables.—According to measurement theory, a neighborhood *factor* based on multiple indicators may be better than a single neighborhood *variable* to measure a latent construct (DeVellis, 2016). A neighborhood variable, however, can be more practical than a neighborhood factor because the meaning of a variable (e.g., poverty rate) is more straightforward than of a factor (e.g., impoverishment). It also confers the advantage of comparability to other works that use simple neighborhood measures. For this reason, the current study built models using neighborhood variables, as well as models using neighborhood factors. We used the following three neighborhood variables as they showed very strong correlations with the above neighborhood factors: *poverty rate* (% persons whose income below the federal poverty level); *mobility rate* (% households moved in the last 5 years); and *child/adult ratio* (ratio of the number of children aged 13 or younger to the number of adults aged 21 or older). When a child made residential moves at a given age, the last neighborhood was used to measure neighborhood factors and variables.

Moving Out of St. Louis.—While all children were residing in St. Louis at baseline, some moved out of St. Louis during follow-up. This variable was considered as indicating a long-distance mobility, which might be more likely to disconnect families from their social supports and networks in their prior residential neighborhoods in St. Louis.

It is worth noting that the CMR likelihood was estimated while following up children from January 1995 (after sampling) to March 2009 (the end of data coverage). Yet, measures of some variables had different timeframes based on their usage in the study (e.g. baseline conditions or later service use). The Supplement further describes timeframes and how other control variables were operationalized and measured (the Measures of Other Control Variables section and Table S3).

Analysis

Multilevel logistic growth curve models estimated the CMR likelihood at each age (Luke, 2008). The multilevel design handled the nested data structure (i.e., multiple observations within children and neighborhoods). The growth curve model considered changes of the likelihood over time by child age. In analyses, continuous variables were centered to their grand mean. The *lme4* package in R was used for the analyses.

Results

Descriptive Statistics

Table 1 reports descriptive statistics. Regarding the observation-level variables, the probabilities of having a CMR at a given age were, on average, 8.3% (the AFDC sample) to 19.7% (the CAN sample). Prior welfare indicated that children were on welfare for 81% (the AFDC sample) to 85% (the CAN sample) of their time by their current age on average. Residential moves showed that over 20% of children moved more than once at a given age. For other observation-level risk factors, the CAN sample were in general more likely to have these factors than the AFDC sample.

The child/family-level baseline characteristics can be seen in Table 1. Both samples had a low socioeconomic status at baseline. The AFDC sample consisted of children who were on AFDC at baseline. Most (91.3%) of the CAN sample also received AFDC at baseline. Black children comprised 76.5% of the CAN sample and 83.6% of the AFDC sample, while Black children comprised 35.1% of the St Louis child population. This higher representation of Black children among the CAN and AFDC samples was consistent with national demographics (Drake et al., 2011). Other minority children comprised a very small proportion (< 3%) in both samples, as well as the St. Louis population.

The neighborhood-level statistics are reported at the observation level (see Table 1). The mean values of neighborhood variables were mostly similar between the CAN and AFDC samples. During the follow-up period, 5.4% of the AFDC sample and 7.1% of the CAN sample moved out of St. Louis while most children remained in St. Louis. Among those moving out of St. Louis, 94% (the CAN sample) to 96% (the AFDC sample) were moved in rural or suburban counties, and 55% (the AFDC sample) to 57% (the CAN sample) moved farther than adjacent counties of St. Louis.

Intraclass Correlation Coefficients

Based on the null model (i.e., the unconditional model with no predictor) of each sample, we calculated intraclass correlation coefficients (ICCs). The child/family-level ICCs were 0.2341 (the CAN sample) and 0.3778 (the AFDC sample), indicating that 23.41% to 37.78% of the variance in the CMR likelihood placed between children/families. The neighborhood-level ICCs were 0.0005 (the CAN sample) and 0.0000 (the AFDC sample), showing that 0.00% to 0.05% of the variance was located between neighborhoods. The rest of the variance (about 60% to 76%) was situated between age-year observations. These results indicated that the CMR risk varied mainly by time and between children (and their families), while the risk varied little between residential neighborhoods.

Model Building

We followed the model-building approach suggested by Raudenbush and Bryk (2002). We started with a simpler model and moved onto a more complex model until observing no meaningful improvement in model fit. We used a model fit indicator, called Akaike Information Criterion (AIC). AIC introduces penalties for more complex models with more parameters to balance parsimony versus model fit. A lower AIC value (lowered by 4 or more) empirically supports a more complex model, while a small reduction (2 or less) or an increase in an AIC value suggests no meaningful improvement in model fit by adding parameters (Burnham & Anderson, 2004). All models were fitted as a multilevel logistic growth curve model.

CAN sample.—Table S4 in the Supplement provides the results of models for the CAN sample. When adding child age (Model 1 → Model 2), observation-level predictors (Model 2 → Model 3), and child/family-level predictors (Model 3 → Model 4) in sequence, model fit was meaningfully improved at each step. There was no meaningful improvement in model fit by adding neighborhood factors (Model 4 → Model 5), neighborhood variables (Model 4 → Model 6), the "race × neighborhood impoverishment" interaction (Model 5 → Model 7), or the "race × neighborhood poverty rate" interaction (Model 6 → Model 8). We observed no meaningful improvement of model fit by adding random slopes and other interactions (e.g., child age × neighborhood poverty). The trimmed model (Model 9) which included only parameters with meaningful contribution to model fit was the most optimal model, supported by AIC.

AFDC sample.—Table S5 in the Supplement shows the results of models for the AFDC sample. There were some interesting differences in results between this sample and the CAN sample with regard to neighborhood characteristics and their interaction with child race. Adding neighborhood factors (Model 4 → Model 5) and neighborhood variables (Model 4 → Model 6) showed meaningful improvement in model fit. Adding the "race × neighborhood impoverishment" interaction (Model 5 → Model 7) and the "race × neighborhood poverty rate" interaction (Model 6 → Model 8) produced no meaningful improvement in model fit. While building a trimmed model, however, the interaction between child race and neighborhood poverty rate became statistically meaningful as the AIC value reduced by 2.1. Although the improvement of model fit was marginal, the final model (Model 10) retained this interaction because of its theoretical interest. We additionally examined random slopes and other interactions (e.g., child age × neighborhood poverty). None meaningfully improved model fit.

Final Models

Table 2 presents the *trimmed* models including only statistically meaningful predictors, as well as the *full* models including all study predictors. We consider the *trimmed* models as the final models since they are the most optimal models. This section reports the results of the *trimmed* models. We report only models with neighborhood variables because interpretations of findings are more straightforward and readily comparable to other study sites, while the choice between neighborhood factors and variables had little influence on the overall model fit.

In the CAN sample, no neighborhood variables were statistically significant, including the interaction terms between child race and poverty rate. The number of residential moves and moving out of St. Louis were also not significant.

In the AFDC sample, neighborhood poverty rate and neighborhood child/adult ratio were significantly associated with the CMR likelihood. For neighborhood poverty rate, the "child race × poverty rate" interaction term suggested that the relationship between neighborhood poverty rate and the CMR likelihood differed by child race. Calculation of race-specific odds ratios needs to consider both the main and interaction terms (see the Race-Specific Odds Ratio section in the Supplement for the underlying calculation). For White children, every 10-percentage-point increase in the neighborhood poverty rate was significantly associated with a 31% increase in the CMR likelihood (OR = 1.31, 95% CI = 1.05-1.64). This relationship was significant neither for Black children (OR = 1.01, 95% CI = 0.92-1.10) nor for Other minority children (OR = 0.56, 95% CI = 0.19-1.60). Regarding child/adult ratio, children in neighborhoods with proportionally more children showed a somewhat lower CMR likelihood (OR = 0.90, 95% CI = 0.82-0.99). While the number of residential moves had no significant association with the CMR likelihood for both samples, moving out of St. Louis was significant in the AFDC sample. After moving out of St. Louis, the CMR likelihood increased by 63% (OR = 1.63, 95% CI = 1.07-2.48).

Prediction Graphs

To clarify the interactions between neighborhood poverty rate and child race, we show the estimated CMR likelihoods by child race categories and neighborhood poverty rates in Figure 1. For the CAN sample, the full model was used instead of the final trimmed model, which excluded all neighborhood variables as none of them were statistically significant.

For the AFDC sample, the final (trimmed) model was used. In the CAN sample, there was no significant association between neighborhood poverty rates and CMR likelihoods for both White and Black children. In the AFDC sample, interactions between child race and neighborhood poverty rate were found. For White children, the CMR likelihood increased with the increase of neighborhood poverty rates, while the likelihood was held almost constant across the levels of neighborhood poverty for Black children. As a result, in high-poverty neighborhoods, White children were at a higher risk of CMR than Black children were while controlling for other predictors. Modeling this interaction between child race and neighborhood poverty, however, had marginal improvement of model fit. This was because White children residing in high-poverty neighborhoods were small in number (Figure 1). Estimates for other minority children are not presented due to the rarity of children fitting this category in the St. Louis population and thus in this study's samples.

Discussion

This study examined neighborhood contextual effects on children's risk of having a child maltreatment report at each age from 1 to 16 years. For the first time, this study considered longitudinal changes of children's residential neighborhoods over time in analysis by following up children during ages with an active AFDC/TANF case.

In the CAN sample, no neighborhood characteristics had a significant association with the risk of maltreatment reporting during the follow-up period. It is possible that for children who have already experienced reported maltreatment (the CAN sample), neighborhood contexts do not further alter their future recurrence risk. Alternately, there may be some unmeasured factor which accounts for this difference.

In the AFDC sample, some neighborhood characteristics were related to risk, independent of child/family characteristics. First, neighborhood poverty was associated with increased risk of maltreatment reporting for White children, while the risk did not vary by neighborhood poverty for Black children. A prior study found a similar interaction (Irwin, 2009). A possible explanation for this interaction is differential sensitivity of racial groups to neighborhood contexts, perhaps due to cultural factors. Several competing explanations are also possible. The first one involves *differential assortment* (Drake et al., 2009). That is, structural advantages for White families may lead to those very few (Drake & Rank, 2009) white families who do fall into extreme poverty areas being a particularly high-risk group, with resultantly higher risk of maltreatment. The second competing explanation is related to the idea of being *out of place* (Drake et al., 2009; McDaniel & Slack, 2005). This idea suggests that when children are numerical minorities in a community (i.e., being out of place), these children may be more visible and thus more reported to CPS. In the current study data, Black children dominated in high poverty neighborhoods while White children dominated in low poverty neighborhoods. Black children in *low* poverty neighborhoods and White children in *high* poverty neighborhoods therefore might show increased report rates by the effect of being out of place. Although this interaction is theoretically interesting, the practical importance seems to be small, as only very few White children reside in high poverty neighborhoods and are subject to this interaction.

While we identified no significant predictive contribution of neighborhood child/adult ratio in the CAN sample, we found that residing in neighborhoods with proportionally more children *lowered* the risk of maltreatment reporting in the AFDC sample. These findings, especially the negative association, was surprising as prior studies using samples from a general population found no association (Freisthler & Wolf, 2016; Irwin, 2009) or a positive association (Coulton et al., 1999; Merritt, 2009). The idea of neighborhood child care burden is that neighborhoods with more adults, who are possible caregiving resources, may have lower rates of child maltreatment. Our findings either do not support this idea (in the CAN sample) or may even stand as evidence against it (in the AFDC sample). The inconsistency between prior and current findings may suggest that the environment of neighborhoods with more children can be more favorable for low-socioeconomic status (SES) families but less favorable for high-SES families. We need more evidence to refine theoretical rationales for neighborhood child care burden (or child/adult ratio) and to advance an understanding of its differential function by family SES and maltreatment risk levels.

Social ties are both seen as important and find empirical support within both the sociological and psychological perspectives, and residential stability is important to build social ties because establishment of social ties is a long term process (Belsky, 1980, 1993; Cicchetti & Lynch, 1993; Sampson et al., 1997, 1999; Sampson & Groves, 1989). Nevertheless, we found that neither family-level instability (i.e., residential moves) nor neighborhood-level instability brought a significant contribution to the risk of maltreatment reporting in both CAN and AFDC samples. Previous evidence in this area was somewhat inconsistent in terms of significance and the outcome of interest (e.g., official report and surveyed maltreatment) (Coulton et al., 1999; Freisthler & Maguire-Jack, 2015; Freisthler & Wolf, 2016; Irwin, 2009; Kim, 2004; Merritt, 2009; Molnar et al., 2003). A prior study using a sample from the general population found neighborhood instability was associated with increased risk of maltreatment reporting (Irwin, 2009). The current study's null finding for high-risk families might suggest that neighborhood instability might be more pronounced among low-risk families.

Regarding long-distance mobility, the current study found that the risk of maltreatment reporting increased after moving out of St. Louis among children who merely received AFDC with no reported maltreatment at baseline (the AFDC sample). This might be because families who moved a long distance may experience dramatic changes due to the disruption of their current life base. Among those moving out of St. Louis, more than half (55%) moved in counties farther away than those counties adjacent to St. Louis. It was also possible, however, that the identified relationship was confounded by urban, suburban, and rural settings as most (96%) of those moving out of St. Louis (urban) moved into rural or suburban counties. This relationship was not found among the CAN sample children who already experienced reported maltreatment at baseline and at high risk of recurrence during follow-up. The overall impact was small, as only very few children moved out of St. Louis (5.4%) during the follow-up period. Again, limited prior evidence prohibits drawing any conclusion with regard to this issue.

Our data limits our ability to interpret why families may move to lower or higher-poverty neighborhoods. Recent work by DeLuca, Wood and Rosenblatt (2019) found that most residential moves by poor Black families were "catalyzed by landlords, housing quality failures, and violence" (p.556), with relatively few moves being due to a desire to improve neighborhood context. The forced nature of these moves resulted in limited options for the moving families, perhaps increasing the chance of moves to higher poverty areas. From a child welfare perspective, this suggests that these exogenously determined moves may add substantial stress to already burdened families, possibly increasing the risk of maltreatment.

This study highlighted the importance of tracing residential neighborhoods in a longitudinal study. While doing so, we identified some neighborhood effects. Yet, these effects were small in contribution to the overall risk and were less observable among more vulnerable children. Our findings have limited generalizability to low-risk families, which may explain some inconsistencies with prior studies. Nevertheless, our findings may be practically and theoretically important as they have strong external validity for high-risk populations.

Strengths and Limitations

This study has several strengths. This is the first study considering both family residential moves and longitudinal changes of residential neighborhoods in analysis to estimate the risk of child maltreatment reporting. This was possible by longitudinally tracing children's residential address using AFDC/TANF records. The use of previously linked administrative data was also a clear strength. This allowed us to measure a wide range of variables, including frequent residential moves over time, with little risk of recall bias. Another strength was the use of multilevel growth modeling. By using this advanced technique, we could select a subset of observations for analysis and continue estimates even after the first child maltreatment report. Finally, this study established clear temporal precedence of neighborhood contexts, residential moves, and other predictors in their relation to the outcome.

Several limitations of this study suggest some caution in interpreting findings. Our findings are associative, not causal. The study samples included only high-risk children who had a child maltreatment report or an AFDC case in early childhood. It is important to recall that this study, by design and due to the limitations of the data, cannot track children unless they are receiving AFDC/TANF. This means that families which permanently exit public assistance are invisible to us, and among those may be families who moved to neighborhoods with more employment opportunities. *In a practical sense, this means that our findings pertain to families who remain in personal financial distress, but move between areas of differing economic advantage*. We can, for example, say nothing about families who permanently exit AFDC. This powerfully shapes the generalizability of the findings. The findings are most generalizable to many high-risk children who face chronic economic and other risk factors. However, generalizability to low-risk children or children intermittently at risk, who may have a larger spectrum of residential mobility and neighborhood conditions, is sharply limited. Analytically, we could not assess spatial autocorrelation since original census tract codes were suppressed to protect confidentiality. This might lead to underestimation of standard errors. Another area of limitation is that while we examined a robust set of neighborhood characteristics, we excluded several characteristics supported by prior studies. Ethnic heterogeneity was not examined as the study site had few immigrant populations. Substance use contexts and neighborhood processes (e.g., collective efficacy) were not examined due to the lack of data. In addition, this study estimated the likelihood of maltreatment *reports*, not all maltreatment *events*. Although findings on reports have important implications for policy and practice, one should not generalize this study's findings to all events. Finally, the study data are vulnerable to the limitations of any administrative records, such as missing or incorrect data.

Implications

This study has theoretical, practical, and research implications. Theoretical perspectives relating to neighborhood contextual effects were not robustly supported by this study for high-risk children with continuing experiences on AFDC/TANF. Compared to prior multilevel studies using samples from a general population, this study found that neighborhood effects were small in contribution to the overall risk among low-SES children (the AFDC sample) and were less observable among children with prior reported maltreatment (the CAN sample). To the degree that our findings are not an artifact of the study limitations, these inconsistencies suggest a need for a new theoretical framework considering possible differences in neighborhood contextual influences by family SES and the prior history of child maltreatment.

This study informs recent community-level prevention efforts. With growing theoretical attention to the role of communities in child maltreatment, community-level prevention programs are gaining popularity (Molnar et al., 2016). Our findings suggest that when we develop and implement community-level prevention programs, we need to consider the effectiveness of those programs among the most vulnerable families.

Our findings suggest the importance of tracing changes of residential neighborhoods in analyses. Moving from one neighborhood to another does not necessarily mean a dramatic change of neighborhood characteristics (e.g., moving into a similar SES neighborhood). Yet, given the frequency of changes in residential neighborhoods, we may need to take such changes into account to improve measurement of "current" neighborhood contexts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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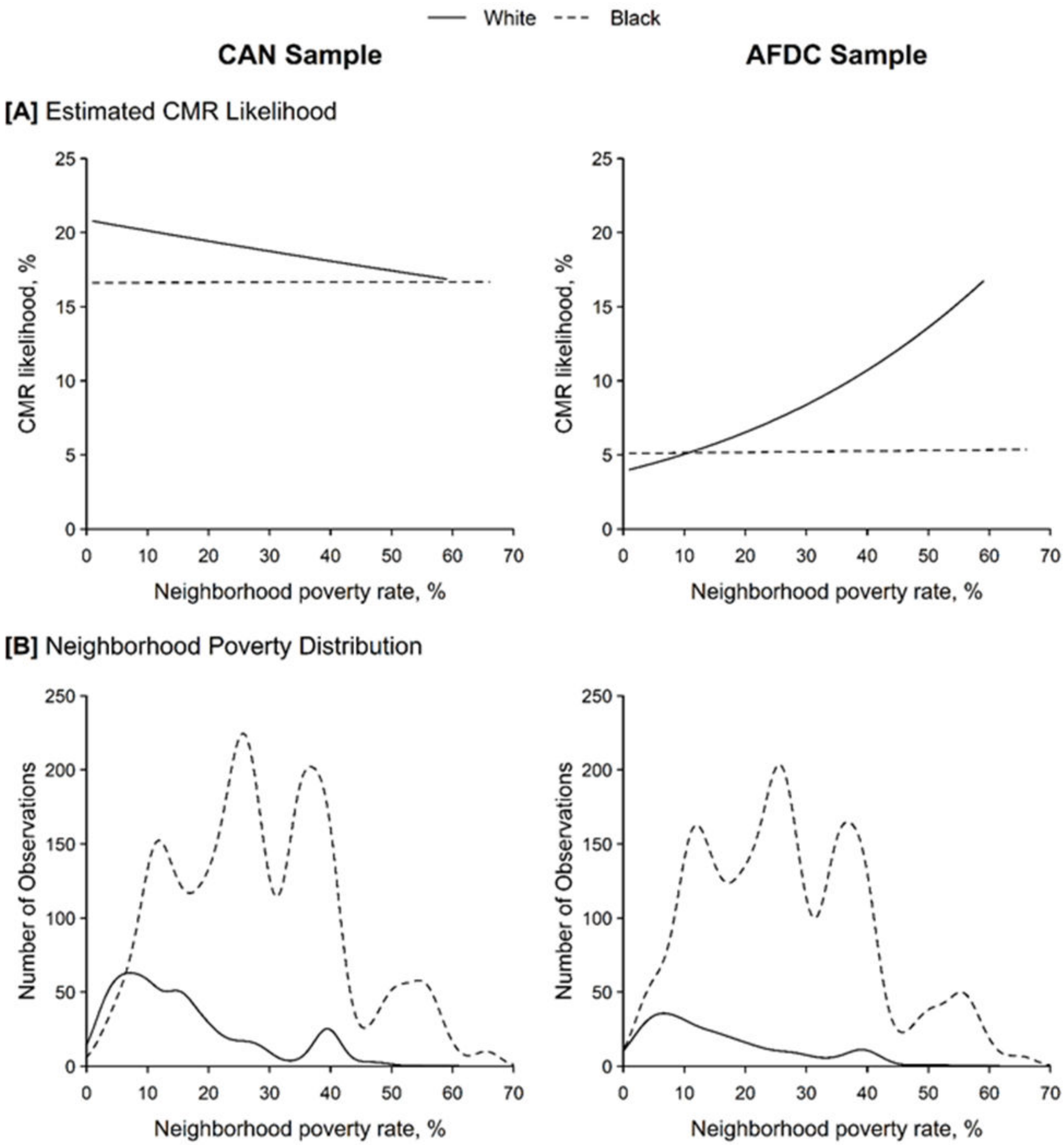

Figure 1.

Race-specific likelihoods of child maltreatment reports [A] and neighborhood poverty distributions [B].

Note: In both [A] and [B] graphs, the solid lines represent data for White children and dashed lines represent data for Black children. The estimated child maltreatment report (CMR) likelihoods for the CAN sample are based on the full model in Table 2 because all neighborhood variables are not statistically significant and therefore excluded from the trimmed final model. It is worth noting that the depicted negative association between neighborhood poverty rates and CMR likelihoods for White children in the CAN sample is not statistically significant. The estimates for the AFDC sample are based on the trimmed final model in Table 2. The estimated CMR likelihoods are presented specific to child race and neighborhood poverty rate while all other variables are fixed to their grand mean. The neighborhood poverty distributions are based on kernel density estimates. The Horizontal ranges of graphs are corresponding race-specific ranges of neighborhood poverty rates.

Table 1.

Variable Description, Data Source, and Descriptive Statistics.

Variables	Description	Data source	% or Mean (SD)	
			CAN sample	AFDC sample
Observation-level			*N_1=7,881*	*N_1=6,907*
Outcome: CMR *	1=having a child maltreatment report (CMR); 0=no	CPS, 1995-2009	19.7%	8.3%
Child age	Current child age (1 to 17; 1 unit=1 year)	Birth, 1991-1994	6.63 (3.38)	6.55 (3.50)
Prior welfare	% months on AFDC/TANF since child's birth	Welfare, 1991-2009	0.85 (0.22)	0.81 (0.23)
TANF no limit	1=receiving TANF after 60-month limit; 0=no	Welfare, 1997-2009	9.2%	6.9%
Prior CPS report	0 prior report	CPS, 1991-2009	-	78.6%
	1 prior report		45.4%	13.6%
	2 prior report		24.8%	4.3%
	3 prior report (3+ for the AFDC sample)		13.2%	3.5%
	4+ prior report		16.6%	-
FCS only	1=prior Family Centered Services only; 0=no	CPS, 1991-2009	24.5%	8.7%
IIS w/ & w/o FCS	1=prior Intensive In-home Services;0=no	CPS, 1991-2009	11.0%	3.1%
Child current injury	1=ER injury record at current age; 0=no	ER, 1997-2009	4.7%	4.4%
Child prior injury	1=ER injury record before current age; 0=no	ER, 1997-2009	21.3%	20.3%
Child mental health	1=ER mental health record, 0=no	ER, 1997-2009	2.9%	1.5%
Child chronic care	1=ER mental delay or chronic/serious health; 0=no	ER, 1997-2009	0.5%	0.3%
Child delinquency	1=JC/arrest record; 0=no	JC/Arrest, 1991-2009	2.2%	1.7%
Child SE	1=special education (SE) record; 0=no	SE, 1991-2006	11.2%	7.5%
Parent conviction	1=conviction record; 0=no	Conviction, 1975-2007	2.3%	1.2%
Parent arrest	1=arrest record; 0=no	Arrest, 1963-2008	9.1%	5.4%
Residential moves *	0 move at current age	Welfare, 1995-2009	76.7%	79.9%
	1 move at current age		20.7%	18.2%
	2+ moves at current age		2.6%	1.9%
Child/family-level			*N_2=1,526*	*N_2=1,436*
Child race *	Non-Hispanic/Latino White	Birth, 1991-1994	22.7%	14.9%
	Non-Hispanic/Latino Black		76.5%	83.6%
	Other minority		0.8%	1.5%
Child birth weight	Normal (≥2.5kg)	Birth, 1991-1994	88.0%	90.6%
	Low (<2.5kg, ≥1.5kg)		10.5%	8.2%
	Very low (<1.5kg)		1.5%	1.2%
Birth year	1991	Birth, 1991-1994	31.1%	28.3%
	1992		33.0%	31.7%
	1993		26.9%	29.7%
	1994		9.0%	10.3%
Child sex	1=female, 0=male	Birth, 1991-1994	48.5%	47.8%
Medicaid at birth	1=on Medicaid at subject child's birth; 0=no	Birth, 1991-1994	69.4%	67.9%
Mom no high school	1=no HS degree at subject child's birth; 0=no	Birth/CPS/AFDC	62.9%	49.0%

Variables	Description	Data source	% or Mean (SD)	
			CAN sample	AFDC sample
Mom teen birth	1=mom < age 20 at subject child’s birth; 0=no	Birth/CPS/AFDC	32.0%	27.9%
Mom foster care	1=mom in foster care during her youth; 0=no	CPS	8.0%	4.3%
Baseline AFDC	1=on AFDC at baseline (for CAN sample); 0=no	Welfare, 1991-1994	91.3%	-
Neighborhood-level			*N_3=385*	*N_3=328*
Poverty rate*	% persons whose income below poverty level	Census, 1990-2009	26.18 (14.01)	25.67 (13.96)
Mobility rate*	% households that moved within last 5 years	Census, 1990-2009	46.79 (12.96)	46.44 (12.86)
Child/adult ratio*	(# children aged 0 to 13)/(# adults aged 21+)	Census, 1990-2009	0.34 (0.13)	0.34 (0.12)
Out of St. Louis*	1=residing out of St. Louis City/County, 0=no	Welfare, 1995-2009	7.1%	5.4%

*The outcome and predictor variables of interest (others are considered as controls). CPS = child protective services. ER = emergency room. JC = juvenile court. Conviction = prison, parole, or probation. SD = standard deviation. N_1 = number of age-year observations. N_2 = number of children. N_3 = number of tracts.

Table 2.

Final Multilevel Logistic Growth Curve Models of Child Maltreatment Report Likelihoods.

	CAN sample (N_1=7,881; N_2=1,526; N_3=385)		AFDC sample (N_1=6,907; N_2=1,436; N_3=328)	
	Full model	**Final model**	**Full model**	**Final model**
Fixed effect	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**
Observation-level				
Child age	**0.89 (0.86-0.92)**	**0.88 (0.86-0.90)**	0.96 (0.91-1.01)	**0.94 (0.91-0.98)**
Prior welfare (1 unit=10 % points)	1.01 (0.98-1.05)	-	0.97 (0.92-1.02)	-
TANF no limit	0.82 (0.61-1.10)	-	0.75 (0.47-1.22)	-
Prior CPS report: 0			Ref	Ref
1	Ref	Ref	**1.50 (1.05-2.12)**	**1.53 (1.09-2.16)**
2	**1.54 (1.31-1.81)**	**1.56 (1.33-1.83)**	**2.14 (1.25-3.64)**	**2.19 (1.30-3.69)**
3[b]	**2.26 (1.85-2.75)**	**2.29 (1.89-2.79)**	**2.56 (1.36-4.82)**	**2.48 (1.34-4.61)**
4[c]	**3.34 (2.70-4.14)**	**3.40 (2.76-4.20)**		
CPS service (ref=None): FCS only	**0.78 (0.67-0.92)**	**0.78 (0.67-0.92)**	**0.64 (0.43-0.96)**	**0.64 (0.43-0.94)**
IIS	1.12 (0.91-1.37)	1.11 (0.90-1.36)	1.54 (0.93-2.57)	1.51 (0.91-2.50)
Child current injury	1.27 (0.97-1.66)	-	**1.71 (1.14-2.56)**	**1.72 (1.15-2.56)**
Child prior injury	0.92 (0.76-1.11)	-	1.01 (0.75-1.38)	1.02 (0.76-1.38)
Child mental health	**1.54 (1.08-2.21)**	**1.58 (1.11-2.24)**	**2.70 (1.34-5.44)**	**2.98 (1.50-5.92)**
Child chronic care	1.23 (0.54-2.81)	-	2.55 (0.60-10.9)	-
Child delinquency	**2.03 (1.34-3.08)**	**1.87 (1.24-2.82)**	1.13 (0.52-2.44)	-
Child special education	1.16 (0.94-1.44)	-	1.09 (0.71-1.66)	-
Parent conviction	0.92 (0.58-1.47)	-	1.48 (0.63-3.45)	-
Parent arrest	1.13 (0.90-1.42)	-	**1.96 (1.28-3.00)**	**2.08 (1.38-3.14)**
Residential moves (ref=0): 1	0.92 (0.79-1.06)	-	0.99 (0.78-1.26)	-
2+	1.16 (0.81-1.64)	-	1.68 (0.97-2.91)	-
Child/family-level				
Child race (ref=White): Black	0.85 (0.69-1.06)	**0.78 (0.66-0.92)**	0.70 (0.48-1.02)	**0.67 (0.46-0.98)**
Other	0.13 (0.02-1.15)	0.34 (0.11-1.01)	**0.19 (0.04-0.98)**	0.20 (0.04-1.01)
Birth weight (ref=Normal)	Reference	-	Reference	-
Birth weight (ref=Normal): Low	1.01 (0.82-1.24)	-	1.18 (0.80-1.75)	-
Very low	0.57 (0.30-1.08)	-	1.20 (0.46-3.11)	-
Birth year (ref=1991): 1992	0.86 (0.73-1.02)	0.87 (0.74-1.02)	1.13 (0.84-1.53)	-
1993	**0.78 (0.65-0.94)**	**0.77 (0.65-0.92)**	1.27 (0.93-1.74)	-
1994	0.86 (0.67-1.12)	0.83 (0.65-1.07)	1.20 (0.77-1.88)	-
Child sex: female	0.93 (0.81-1.06)	-	0.97 (0.77-1.22)	-
Medicaid at birth	0.88 (0.76-1.02)	-	0.93 (0.72-1.20)	-
Mom no high school	**1.35 (1.16-1.57)**	**1.33 (1.15-1.54)**	**1.63 (1.26-2.10)**	**1.58 (1.25-2.01)**
Mom teen birth	**0.85 (0.74-0.99)**	**0.85 (0.74-0.99)**	1.00 (0.78-1.30)	-
Mom foster care	**1.35 (1.08-1.69)**	**1.35 (1.08-1.69)**	**1.78 (1.10-2.86)**	**1.78 (1.11-2.87)**
Baseline AFDC (CAN sample only)	1.06 (0.80-1.40)	-		

	CAN sample (N_1=7,881; N_2=1,526; N_3=385)		AFDC sample (N_1=6,907; N_2=1,436; N_3=328)	
	Full model	**Final model**	**Full model**	**Final model**
Fixed effect	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**	**OR (95% CI)**
Neighborhood-level				
Out of St. Louis	1.24 (0.96-1.60)	-	**1.54 (1.01-2.36)**	**1.63 (1.07-2.48)**
Poverty rate (1 unit=10 % points)	0.96 (0.84-1.09)	-	**1.25 (1.00-1.57)**	**1.31 (1.05-1.64)**
Child race: Black × poverty rate	1.05 (0.92-1.20)	-	0.80 (0.63-1.01)	**0.77 (0.61-0.97)**
Child race: Other × poverty rate	0.36 (0.08-1.49)	-	0.42 (0.14-1.25)	0.43 (0.14-1.25)
Mobility rate (1 unit=10 % points)	1.01 (0.95-1.07)	-	1.08 (0.99-1.18)	-
Child/adult ratio (1 unit=0.1)	1.02 (0.95-1.08)	-	**0.90 (0.82-0.99)**	**0.90 (0.82-0.99)**
Random Effect	Variance	Variance	Variance	Variance
Child/family-level intercept	.1917	.1945	.8820	.8999
Neighborhood-level intercept	.0139	.0145	.0000	.0000
Model fit	Value	Value	Value	Value
Akaike information criterion (AIC)	7419.3	7403.5	3730.8	3711.9

Note: N_1 = number of age-year observations. N_2 = number of children. N_3 = number of tracts. Ref = reference group. OR = odds ratio. CI = confidence interval. Significant odds ratios (p < .05) are in boldface.