Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

HHS Public Access

Author manuscript

*Child Abuse Negl*. Author manuscript; available in PMC 2023 November 15.

Published in final edited form as:

*Child Abuse Negl*. 2023 September ; 143: 106333. doi:10.1016/j.chiabu.2023.106333.

# Has the Relationship between Community Poverty and Child Maltreatment Report Rates Become Stronger or Weaker Over Time?

**Hyunil Kim**[1,*], **Brett Drake**[2]

[1]School of Social Work, University Illinois at Urbana-Champaign, Urbana, Illinois.

[2]Brown School of Social Work, Washington University in St. Louis, St. Louis, Missouri

## Abstract

**Background:** Poverty is among the most powerful predictors of child maltreatment risk and reporting. To date, however, there have been no studies assessing the stability of this relationship over time.

**Objective:** To examine whether the county-level relationship between child poverty rates and child maltreatment report (CMR) rates changed over time in the United States in 2009–2018, overall and across of child age, sex, race/ethnicity, and maltreatment type.

**Participants and Setting:** U.S. Counties in 2009–2018.

**Methods:** Linear multilevel models estimated this relationship and its longitudinal change, while controlling for potential confounding variables.

**Results:** We found that the county-level relationship between child poverty rates and CMR rates had intensified almost linearly from 2009 to 2018. Per one-percentage-point increase in child poverty rates, CMR rates significantly increased by 1.26 per 1,000 children in 2009 and by 1.74 per 1,000 children in 2018, indicating an almost 40% increase in the poverty-CMR relationship. This increasing trend was also found within all subgroups of child age and sex. This trend was found among White and Black children, but not among Latino children. This trend was strong among neglect reports, weaker among physical abuse reports, and not found among sexual abuse reports.

**Conclusions:** Our findings highlight the continued, perhaps increasing importance of poverty as a predictor of CMR. To the degree that our findings can be replicated, they could be interpreted as supporting an increased emphasis on reducing child maltreatment incidents and reports through poverty amelioration efforts and the provision of material family supports.

## Introduction

Child maltreatment is a national concern. Each year, almost 1 in 20 U.S. children are reported to child protective services (CPS) for alleged child maltreatment and receive

*Corresponding Author: Hyunil Kim (hyunil@illinois.edu; T. 217-300-8122; address: 1010 W Nevada St, Urbana, IL 61801).

Declarations of interest: none

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

an CPS investigation or assessment (U.S. DHHS, 2021). This high annual risk leads to high cumulative risk. From birth to the end of childhood, roughly 1 in 3 U.S. children are expected to have at least one investigated or assessed child maltreatment report (hereafter just "CMR"; Kim et al., 2017). Substantial evidence suggests that children with maltreatment experiences have increased risks of many negative outcomes, such as developmental, cognitive, emotional, behavioral, and health problems (Anda et al., 2006; Vaithianathan et al., 2018). Research consistently shows that poverty is a strong risk factor for child maltreatment (Drake et al., 2022; Pelton, 2015). Poverty has been used to identify high-risk families and communities, allowing prevention and treatment resources to be allocated to those in need (Daley et al., 2016; Drake et al., 2022). In addition, prevention efforts are increasingly focused on providing cash and near-cash transfer programs to mitigate the impact of poverty on child maltreatment (Pac et al., 2023). However, a significant knowledge gap remains regarding whether the strength of the poverty-maltreatment relationship has changed over time.

Understanding whether the strength of the poverty-maltreatment relationship has shifted over time is important for several reasons. First, if the relationship has remained strong or has even strengthened over time, it would reinforce the need to address socioeconomic disparities in child maltreatment. Our findings could serve as empirical evidence to raise awareness and identify possible solutions for addressing this pressing social justice issue. Second, if the relationship has changed, and poverty has become an even more significant factor, there are implications for service delivery, as resources should be provided for economically at risk populations. This is particularly vital given the growing interest in the use of predictive analytics, which aim to identify high-risk populations based on specific weights on risk factors for greater precision (Daley et al., 2016; Vaithianathan et al., 2018). Third, if the relationship has persisted or become even stronger over time, then implementing strategies to address poverty would become more appealing options in preventing child maltreatment, assuming a causal relationship, which appears increasingly credible (Drake et al., 2022; Pelton, 2015). Fourth, examining the longitudinal change in the strength of the poverty-maltreatment relationship fills a critical knowledge gap. To our knowledge, no previous studies have explored this topic. Prior longitudinal studies have investigated the relationship between past economic conditions and future maltreatment risk, as well as whether an increase in poverty over time led to a higher risk of maltreatment (e.g., Conrad-Hiebner & Byram, 2020). However, these studies did not explore whether the strength of the poverty-maltreatment relationship has changed over time, either becoming stronger, weaker, or remaining stable. This is a fundamentally distinct question. Obtaining this knowledge would enhance our understanding of the ecology of child maltreatment, where poverty is a crucial dimension.

This study seeks to address the current knowledge gap by examining whether the strength of the relationship between poverty, as defined by being below the federal poverty level, and CMR has changed over time. Our aim is to provide national-level evidence to inform large-scale policies. To achieve this, we examine the cross-sectional relationship between poverty and CMR rates at the county level in the United States for each year from 2009 to 2018.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

## Background

This section provides an overview of prior research on poverty and CMR, as well as broader economic and maltreatment indicators. This review aims to assess the consistency of previous findings on poverty and CMR with a wider range of evidence and support the focus of our study on the relationship between poverty and CMR at the county level.

Longitudinal studies exploring temporal relationships between economic conditions and child maltreatment are increasingly common (Conrad-Hiebner & Byram, 2020). Three primary findings have emerged from these studies. First, prior longitudinal research has found that poor economic conditions in the past are linked to an increased risk of maltreatment in the future (e.g., Irwin, 2009; Putnam-Hornstein & Needell, 2011). This type of research contributes to establishing the temporal ordering between economic conditions and maltreatment risk. Second, research has shown that longer-term exposure to poor economic conditions is associated with an increased risk of maltreatment (e.g., Kim & Drake, 2017; Ovwigho et al., 2003). These findings help clarify the potential role of chronic poverty in child maltreatment. Finally, studies using fixed-effects modeling have found that a decrease in economic conditions over time is related to an increase in maltreatment risk over the same period (e.g., Slack et al., 2007; Yang, 2015). While still susceptible to time-varying confounders, this approach controls for all time-constant characteristics, providing stronger causal evidence than a cross-sectional approach. Despite this prior longitudinal research on the relationship between economic conditions and maltreatment risk, it is still unclear whether the strength of this relationship has changed over time. This study aims to fill this knowledge gap by examining how the strength of the poverty-CMR relationship has varied annually from 2009 to 2018.

Numerous studies have established strong relationships between poverty and CMR at various ecological levels. Studies conducted at the individual level indicate that children who participate in means-tested programs (as poverty proxies) are multiple times more likely to experiencing CMR than non-participants (Irwin, 2009; Putnam-Hornstein & Needell, 2011). Similarly, community-level studies have also found strong relationships between poverty rates and CMR rates across various community levels, such as block groups, census tracts, zip codes, and counties (Coulton et al., 2007; Freisthler et al., 2006; Kim & Drake, 2018; Maguire-Jack, 2014). Our focus is on the county-level relationship between poverty and CMR for several reasons. First, the National Child Abuse and Neglect Data System (NCANDS), which is the national CMR data system, lacks valid economic indicators. The NCANDS provides three binary indicators that are relevant to poverty, including inadequate housing conditions, financial problems, and public assistance receipts. However, these indicators are poorly measured and often report implausible rates of 0% in many states (Kim et al., 2018). This makes it challenging to national NCANDS data to capture the poverty-CMR relationship at the individual level. Instead, we utilize the county identifiers provided by the NCANDS (i.e., a child’s county of residence) to aggregate the NCANDS data at the county level (i.e., county CMR rates). By doing so, we can use Census data’s county poverty rates to examine the county-level relationship between poverty and CMR rates. Secondly, as mentioned earlier, individual-level studies and studies at smaller geographical levels (e.g., census tracts) have been conducted to examine the poverty-CMR relationship.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

However, these studies require linking state or local CMR data with other administrative data (e.g., means-tested program data) or aggregating them into smaller areas. Such linkages and aggregations are rare for most states and local regions, and for national data, it is not possible due to confidentiality restrictions. Examining the county-level relationship between poverty and CMR provides a unique opportunity to study this issue on a larger scale, using easily accessible national data (i.e., NCANDS). Finally, while counties are less homogeneous than smaller areas in terms of economic conditions and other characteristics among their residents (Aron et al., 2010), a growing number of researchers have used counties as their level of analysis. Studies have found that increased county poverty rates were associated with increased county rates of CMRs (Kim & Drake, 2018; Smith et al., 2021) and substantiated CMRs (Eckenrode et al., 2014; Zhang et al., 2021). These studies show that county-level research can be helpful in understanding ecological contexts of child maltreatment. However, a notable knowledge gap remains, as none of these county-level studies have examined changes in the strength of the poverty-CMR relationship over time. We address this gap by examining annual variations in the strength of the poverty-CMR relationship using national county-level data spanning a decade, from 2009 to 2018.

Prior studies based on survey data found strong relationships between broader economic and maltreatment indicators. For example, the National Incidence Study (NIS) of Child Abuse and Neglect provides rates of children endangered by maltreatment based on CPS records and surveys with community professionals to assess both reported and unreported maltreatment incidents in the United States (Sedlak et al., 2010). The fourth and most recent NIS, using data from 2005 to 2006, assessed low socioeconomic status (i.e., household income < $15,000, parental education less than high school, or participating in a poverty program) and found that the endangerment rate among children in low SES households was about 6 times higher than the rate among those not in low SES households (Sedlak et al., 2010). Berger (2004) also used survey data, which measuring child maltreatment based on self-reported measures of no medical checkup, no dentist, low cognitive stimulation, low emotional support, and excessive spanking from the National Longitudinal Survey of Youth. Berger (2004) found that higher income was significantly related to decreased maltreatment risk.

Survey data, particularly the NIS, may include both reported and unreported incidents of maltreatment, although it does not capture all incidents, for example, incidents known only to friends or neighbors and not reported. This provides a significant advantage as compared to CMR data, which are limited to reported incidents only. However, this study does not employ survey data because most longitudinal survey data on economic conditions and maltreatment are panel or cohort data, following the same group of individuals over time, and use relatively small sample sizes (Conrad-Hiebner & Byram, 2020). For our study, we require trend data obtained from a new nationally representative sample or the entire population each year for multiple years. The NIS has been conducted on several occasions with a new nationally representative sample for each one. However, the NIS has been conducted only about once per decade and is outdated, with the most recent two datasets being collected in 1993 and 2005–2006. On the other hand, the NCANDS provides routinely collected population-level records of CMR data for the entire United States over several

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

decades until recent years, allowing us to construct national county-level data that is suitable for our study.

### Current Study

This study examines for the first time, to the best of our knowledge, whether the strength of the county-level relationship between child poverty rates and CMR rates has changed over time, using longitudinal county-level data across 50 U.S. states and the District Columbia (DC) from 2009 to 2018. In more technical terms, we examine an interaction (or moderating) effect of time (i.e., year) on the poverty-CMR relationship. Our primary focus is on investigating the relationship between child poverty rates and overall CMR rates (i.e., rates among all children). Additionally, we explore the relationship between poverty and CMR rates for specific child age groups (i.e., 0–5, 6–11, and 12–17 years old), child sex (i.e., male and female children), race/ethnicity (i.e., White, Black, and Latino children), and maltreatment type (i.e., neglect, physical abuse, and sexual abuse).

## Methods

### Data and Sample

The data for the dependent variables were obtained from the National Child Abuse and Neglect Data System Child Files, the federal repository of all official CMRs (i.e., child maltreatment cases reported to and screened-in by CPS for an investigation/assessment) in the United States. We used all official CMRs from 50 states and DC but excluded CMRs from Puerto Rico due to considerable regional differences between U.S. states and territories. Reported but screened-out cases were only available as state-level aggregate counts and could not be used for this county-level study. Some available evidence based on single-state data (e.g., Putnam-Hornstein & Needell, 2011) suggests that screened-in and -out CMRs are similar in their relationship with poverty. We used the records of all screened-in official CMRs (hereafter, just CMRs) that were made in fiscal years 2009–2018 from the 2009–2019 Child Files.

This study used all CMRs, including both substantiated and unsubstantiated CMRs. Substantiation means that a CPS investigation finds enough evidence to confirm the occurrence of a child maltreatment incident. Yet, a strong body of research has found essentially no difference between children with substantiated and unsubstantiated CMRs in terms of a broad range of future outcomes, such as academic achievement and problems (e.g., reading, math, absence, retention, drop-out, and delinquency), behavioral problems, adaptive behaviors, mental health problems (e.g., anxiety, depression, anger, post-traumatic stress, and dissociation), developmental skills, and child maltreatment recidivism (Hussey et al., 2005; Kohl et al., 2009; Leiter et al., 1994). This suggests that substantiation decisions cannot be used as a proxy for severity or future risk (Drake, 1996). Only about 20% of CMRs are substantiated (U.S. DHHS, 2021), this number decreasing over time, partly as a function of historical policy trends, such as the proliferation of differential response systems. Limiting the sample to substantiated CMRs is therefore likely to lead to serious underestimation of child maltreatment rates and not reduce false positives. Worse, national

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

decreases in substantiation rates (as distinct from report rates) may introduce confounding due to systemic changes such as adoption of differential response.

This study excluded 2.34% of CMR records due to duplicate records (0.06%), missing or out-of-range child ages (0.75%), suppressed state and county identifiers for fatal cases (0.03%), missing county identifiers (0.29%), and potential entry errors of county identifiers for records from GA 2009–2011, PA 2009–2014, and TN 2009 (1.21%). After this management, there were 31,702,456 children with a CMR in 2009–2018. These are unduplicated counts, with a child counted no more than once per year. We aggregated these children into county-year observations (county-years) to compute CMR rates per county per year. There were 32,215 county-years in 2009–2018 (about 3,222 counties × 10 years). We excluded some of these county-years because no record submissions were made (185 county-years from ND 2009, OR 2009–2011, and MA 2009–2018) and because of potential entry errors of county identifiers (984 county-years from GA 2009–2011, PA 2009–2014, and TN 2009). The final data included 96.37% of all county-years in United States from 2009 to 2018.

The Child Files suppressed identifiers of counties with less than 1,000 CMRs per year to protect confidentiality. This suppressed many low-populated counties, but state identifiers of suppressed counties were still available. To use suppressed counties in the analyses, we combined them into a joint county area per state using their state identifiers. In our data, 5,697 county-years were unsuppressed, and 25,349 county-years were suppressed. We combined these suppressed county-years into 456 joint county-years. This aggregation allowed us to use all data for the analyses. A drawback was that a joint county area represented many low-populated, mostly rural counties in a state. Yet, large rural areas were unsuppressed, allowing many states to have multiple rural counties for the analyses. The final data had 6,153 county-years (5,697 unsuppressed county-years + 456 joint county-years), which were nested in 639 counties (and joint counties) and again nested in 50 states and DC. While a large majority of counties are suppressed in any given year, a large majority of the population of the United States does not reside in suppressed counties in any given year, as most people live in large population counties. In the final data, about 76% of U.S. children lived in unsuppressed counties each year.

We obtained all independent and control variables, except for urbanicity, from the American Community Survey (ACS) 5-year estimates. To link ACS data with CMR data, we identified the 5,697 ACS county-years (that were unsuppressed in CMR data) and the 25,439 ACS county-years (that were suppressed in CMR data). Then, we combined the 25,439 ACS county-years into 456 joint county-years as we did for the suppressed counties in CMR data. We assigned population-weighted means for ACS joint county-years. For example, we computed the population-weighted mean of child poverty rates of county-years that were combined into a joint county-year and assigned the mean to that joint county-year. We linked ACS 5-years estimates to 1-year CMR rates by mid-year (e.g., ACS 2007–2011 estimates to 2009 CMR rates; ACS 2016–2020 estimates to 2018 CMR rates). We used the U.S. Department of Agriculture Rural-Urban Continuum Codes to measure urbanicity (USDA ERS, 2020). These codes are updated infrequently, and we used the most recent (2013) codes available.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

We used *1-year* CMR rates but used ACS *5-year* estimates (i.e., 5-year averages) of child poverty rates. Although ACS 1-year estimates may be more sensitive to annual fluctuations, they have large random variations due to small sample sizes. For this reason, ACS data do not provide 1-year estimates for counties with < 60,000 residents (i.e., about 75% of U.S. counties). The ACS 5-year estimates cover all U.S. counties and are more reliable (i.e., smaller random variations). Given the current limitations of ACS data, it is uncertain whether 1-year or 5-year estimates are more suitable for a longitudinal study like ours. Addressing this question comprehensively requires a rigorous measurement study, which is beyond the scope of this study. We did conduct a sensitivity analysis by comparing 1-year and 5-year estimates of child poverty rates in their relationships with CMR rates among counties with non-missing 1-year estimates. While these counties covered only about 25% of U.S. counties, they covered 86% of county-years (5292 of 6150 county-years) in our data as many low-populated county-years were combined into joint county-years in our data. In a nutshell, the longitudinal change in the poverty-CMR relationship was consistent between 1-year and 5-year estimates, and the model fit was better when using 5-year estimates (see Table S1 in the Supplement). Due to the better data coverage, the consistency in results, and the better model fit, we used ACS 5-year estimates.

## Measures

We measured CMR rates (numbers of children with a CMR per 1,000 children) per county per year from 2009 to 2018. We constructed 12 dependent variables: one for overall, three for age-specific (age 0–5, age 6–11, age 12–17), two for child sex-specific (male and female), three for race/ethnicity-specific (White, Black, and Latino), and three for type-specific (neglect, physical abuse, and sexual abuse) CMR rates. We measured Latino (Latino/Hispanic) as *Latino including all races*, White as *non-Latino White alone*, and Black as *Latino and non-Latino Black alone*, consistent with the ACS categorization in order to link CMR rates with ACS child poverty rates. We fit separate models for each dependent variable.

We measured child poverty rates (percentages of children in poverty) per county per year from 2009–2018. We used overall child poverty rates to model overall, sex-specific, and type-specific CMR rates. Since child poverty rates were very different by child age and race/ethnicity, we used age-specific child poverty rates for age-specific CMR rates and race/ethnicity-specific child poverty rates for race/ethnicity-specific CMR rates.

Prior research has identified various community risk/protective conditions for CMRs other than economic conditions. Communities with proportionally more children, more elderly persons, more male adults (i.e., proportionately fewer female adults), and more children with disabilities may have higher care burden and higher CMR rates (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014). Residential instability (i.e., high rates of residential moves) is associated with increased CMR rates (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014), possibly through attenuated social cohesion. Rural and small urban areas have higher rates of both child poverty and CMR than urban areas, which can confound the poverty-CMR relationship (Maguire-Jack & Kim, 2021). Some emerging evidence suggests that communities with more racial/ethnic minorities (i.e., higher

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

percentages of Black, Latino, and foreign-born residents) have lower CMR rates while controlling for economic conditions (Kim & Drake, 2018; Putnam-Hornstein et al., 2013). We controlled for these community conditions in the analyses. The specific measures used for our control variables are reported in Table 1. For parsimony and to maintain larger cell sizes, we combined the original nine Rural-Urban Continuum codes into large urban (code 1: metro areas with ≥ 1 million population), small urban (codes 2–3: metro areas with < 1 million population), and rural (codes 4–9: nonmetro areas).

### Analysis

Linear multilevel models estimated the associations between child poverty rates and CMR rates while adjusting for the control variables. A state random effect was used to handle the nesting of counties in states. The models included year-fixed effects (i.e., year dummies: Y2010, Y2011, …, and Y2018; reference year = 2009) to handle multiple observations and overall longitudinal trends in CMR rates. The models also included the interactions between child poverty rates and year dummies (Poverty × Y2010, Poverty × Y2011, …, and Poverty × Y2018) to examine how the child poverty coefficient in each year from 2010 to 2018 differed from the child poverty coefficient in 2009.

Among 6,153 county-years, three county-years showed CMR rates (> 270 per 1,000) that were exceptionally high (i.e., outside the 4.5 interquartile range) compared to those of other county-years (ranging from 5.1 per 1,000 to 206.9 per 1,000). We excluded these outliers from the overall, sex-specific, and age-specific analyses. Among 6,153 county-years, type-specific analyses also excluded a few outliers (outside the 4.5 interquartile range): two county-years for neglect, 34 county-years for physical abuse, and six county-years for sexual abuse. Some county-years have too few Black or Latino children to provide reliable measures of Black or Latino CMR rates. Among 6,153 county-years, we excluded 521 county-years with < 300 Black children from the Black-specific analysis and 63 county-years with < 300 Latino children from the Latino-specific analysis. We tried 300-, 500-, and 1,000-person cutoff points and found little difference in estimates between them (see Table S2 in the Supplement for details). We used the 300-cutoff point as this allowed for the least degradation in sample size. We further excluded a few outliers (outside the 4.5 interquartile range) from the race/ethnicity-specific analyses: one county-year for White, 19 county-years for Black, and eight county-years for Latino.

For some models of less frequent outcomes (e.g., Black CMR rates, physical abuse report rates, and sexual abuse report rates), their residuals were somewhat positively skewed (skewness > 1). We conducted sensitivity analyses using negative binomial multilevel models and found that their results were consistent with those of linear multilevel models. We report the results of the linear multilevel models (Tables 2 and 3). We used the *lme4* package in R for analysis.

## Results

Table 1 shows descriptive statistics. The rightmost column reports grand means and standard deviations throughout 2009–2018. The left 10 columns report annual means for each year from 2009 to 2018. Overall, 57.1 per 1,000 children had a CMR per county per year on

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

average. Longitudinally, the annual mean of county CMR rates increased almost linearly from 52.9 per 1,000 in 2009 to 62.1 per 1,000 in 2018. County CMR rates were generally higher among younger children. Male and female children showed similar county CMR rates on average. By race/ethnicity, county CMR rates were generally much higher among Black children than among White and Latino children. Neglect report rates in counties were generally much higher than other maltreatment types.

The annual mean of county child poverty rates increased from 20.1% in 2009 to 22.3% in 2012. Then, it decreased to 18.0% in 2018. Overall, 20.6% of children were in poverty per county per year. Younger children had higher county child poverty rates generally. Black and Latino children had far higher county child poverty rates than White children on average.

Table 2 reports the unadjusted coefficients of child poverty rates on CMR rates. Table 3 reports the adjusted coefficients. Each column is based on a separate model for each dependent variable (i.e., each of total and subgroup-specific CMR rates). The first 10 rows report the main term (i.e., the coefficient in 2009) and the interaction terms each year from 2010 to 2018 (i.e., the difference in the coefficient between the given year and 2009). The asterisks in the first row indicate whether the given main term is significant (i.e., whether the association between child poverty rates and CMR rates in 2009 is significant). The asterisks from the second to 10th rows indicate whether the given interaction term is significant (i.e., whether the coefficient in the given year significantly differs from that in 2009). The last 10 rows report coefficients from 2009 to 2018, computed from the main and interaction terms in the first 10 rows. For example, the child poverty coefficient in 2009 on total CMR rates is 1.11 (11th row), which is equal to the main term (1st row). The child poverty coefficient in 2018 on total CMR rates is 1.67 (20th row), which is the sum of the main term in the 1st row (1.11) and the “Child Poverty × Year 2018” interaction term in the 10th row (0.56). The asterisks in the last 10 rows indicate whether the coefficient in the given year is significant (i.e., whether the association between child poverty rates and CMR rates is significant in the given year). The superscript letters of “a” and “b” in the last 10 rows indicate whether the coefficient in the given year significantly differs from 2009.

While not adjusting for the control variables (Table 2), child poverty rates were significantly associated with total and all subgroup-specific CMR rates in all years. These associations became stronger in more recent years. The child poverty coefficient on total CMR rates in 2009 was 1.11. This indicated that per 1-percentage-point increase in child poverty rates, total CMR rates significantly increased by 1.11 per 1,000. The coefficient decreased to 1.02 in 2010. Subsequently, it increased almost linearly each year and reached to 1.67 in 2018. Although the coefficients in 2010–2014 did not significantly differ from the 2009 coefficient (perhaps due to the gradual nature of the change), the coefficients in 2015–2018 did.

The trend in the unadjusted coefficients was consistent by age and sex, but it differed by race/ethnicity and maltreatment type. Regarding race/ethnicity, both the White- and Black-specific coefficients almost linearly increased over time. The child poverty coefficient on White CMR rates increased from 2.24 in 2009 to 3.01 in 2018, a 0.77 increase. During the same period, the child poverty coefficient on Black CMR rates increased by 0.87 from 0.49 to 1.36. For Black CMR rates, the increase of the child poverty coefficient (from the

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

2009 coefficient) was marginally significant in 2011 and significant in 2012 and later years. This was earlier than the White-specific trend (significant increases in 2016–2018). The child poverty coefficient on Latino CMR rates showed little increase over time. Only the 2014 coefficient was significantly larger than the 2009 coefficient, while the coefficients in all other years did not significantly differ from the 2009 coefficient. For maltreatment type, the child poverty coefficients on neglect and physical abuse report rates increased over time, but the child poverty coefficient on sexual abuse report rates showed no significant change over time.

The adjusted coefficients in Table 3 showed longitudinal trends similar to those of the unadjusted coefficients in Table 2, suggesting that the longitudinal trends were robust to potential confounding variables. While adjusting for the control variables (Table 3), the child poverty coefficient increased in an almost linear fashion from 1.26 in 2009 to 1.74 in 2018, except for a slight decrease to 1.17 in 2010. All age- and sex-specific trends were similar to this total trend. For race/ethnicity, both the White- and Black-specific coefficients showed strong increasing trends from 2009 to 2018. The White-specific coefficient increase by 0.81 from 1.54 to 2.35. The Black-specific coefficient increased by 0.92 from 0.33 to 1.25. Significant increases in the coefficients were earlier for the Black-specific trend (since 2011) than the White-specific trend (since 2016; marginally since 2014). The child poverty coefficient on Latino CMR rates mostly showed no increasing trend, with only the 2014 coefficient being significantly larger than the 2009 coefficient. Regarding maltreatment type, The trend for physical abuse was somewhat weaker than the trend for neglect, but still increased. The trend for sexual abuse was almost flat, showing no significant increase over time.

We depict the longitudinal trends of the adjusted child poverty coefficients in Figure 1. As can be seen, the child poverty coefficients on total, sex-specific, and age-specific CMR rates showed similar increasing trends over time. The race/ethnicity- and type-specific trends were somewhat different, as described above. For a deeper exploration of the “Child Poverty × Year” interaction, we depict the expected CMR rates by child poverty rates in 2009 and 2018 while adjusting for the control variables (Figure 2). The 2018 slope is notably steeper than the 2009 slope, suggesting that the county-level relationship between child poverty rates and CMR rates became stronger in more recent years. The graphs also show that this longitudinal increase in the slope is mainly due to the far larger increases in CMR rates among higher-poverty counties over time, while lower-poverty counties had much smaller increases in CMR rates over time.

## Discussion

To examine whether the county-level relationship between child poverty rates and CMR rates changed over time, we analyzed longitudinal county-level data across 50 states and DC from 2009 to 2018. We found that the county-level relationship between child poverty rates and CMR rates not only was strong and significant in all years, but also became stronger over time. This concerning trend was evident in the presence and absence of control variables, not only overall, but also within most subgroups of child age, sex, race/ethnicity, and maltreatment type. This suggests that the trend was robust to the control variables

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

and consistent in most subpopulations. This study used 1-year CMR rates and 5-year child poverty rates. To ensure the robustness of our findings between 1-year and 5-year measures, we conducted a sensitivity analysis, which yielded consistent results regardless of whether we used 1-year or 5-year child poverty rates. This suggests that our findings are unlikely to be powerfully impacted by these measurement issues.

There are several possible reasons for the recent strengthening of the association between child poverty rates and CMR. The first is the impact of the Great Recession on the size of the poverty population. As shown in Figure 3, the number of U.S. children in poverty increased during the recession period and reached a peak of slightly over 16 million in 2010. That number decreased during the recovery period and dropped to below 12 million by 2018. If the 2008 recession had not occurred, perhaps 4 million children might not have fallen into poverty. This population might have had lower CMR risks than those who would have been in poverty without that downturn, as parental traits associated with not being in poverty are often similar to characteristics consistent with good parenting (e.g., good impulse control and good mental health; Drake et al., 2021). Perhaps lower-risk children temporarily entered poverty due to the Great Recession and expanded the child poverty population prior to 2010 (Figure 3). This inflow of lower-risk children would lower the overall CMR risk level among the child poverty population. The presumably lower-risk children exited poverty during the recovery period, gradually from 2010 to 2014 and more rapidly from 2014 to 2018 (Figure 3). This outflow of lower-risk children could increase the poverty-CMR relationship. The child poverty coefficient on the CMR rate in our data indeed increased gradually from 2010 to 2014 and more rapidly from 2014 to 2018 (Figure 1). The literature is sparse on differences in CMR risks between families in temporary poverty (e.g., poverty due to an economic crisis) and in persistent poverty. However, some relevant studies have been conducted. While a study on the latent transition of economic insecurity suggested that the association between long-term economic insecurity and harsh parenting was intricate (Conrad et al., 2019), prior research identified that children more persistently in poverty had higher risks for low education, poor health, unstable employment, and teen birth (Chung & Maguire-Jack, 2020). Some child maltreatment studies also found that a longer stay in poverty-related programs (e.g., AFCD/TANF or Medicaid) was associated with an increased CMR risk (Kim & Drake, 2017; Ovwigho et al., 2003).

The second possible reason is that the increase of the child poverty coefficient is partly due to an actual increase of the poverty impact on child maltreatment. We suggest this because the first reason may contribute to but does not fully explain our findings. As lower-risk children move out of poverty, their CMR risks would decrease even further, which would in turn lower the national CMR rate. Therefore, if the increase of the child poverty coefficient simply reflected the outflow of lower-risk children from the child poverty population, the national CMR rate would presumably decrease during the recovery period. However, the CMR rate markedly increased during the recovery nationally (Kim & Maguire-Jack, 2021), especially in high-poverty counties (Figure 2). The simplest explanation for this is that the impact of poverty on child maltreatment has actually increased over time. An increased poverty impact on child maltreatment would increase the poverty-CMR relationship and also drag up the national CMR rate, despite the decrease of the overall poverty population. The substantial and steady increase in income and wealth inequalities

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

in the United States over the last several decades suggests deterioration in economic conditions among families at the bottom of the income and wealth distributions (Kuhn et al., 2020; Semega & Kollar, 2022). Worsening economic conditions could intensify poverty's impact on maltreatment (Drake et al., 2022; Pelton, 2015). Accepting the impact of the Great Recession in increasing temporary poverty as the sole explanation requires more complicated assumptions to reconcile with the clear longitudinal increase in the national CMR rate in the recovery period. Further research is needed to establish the degree to which the first reason contributes to the longitudinal increase in the poverty-CMR relationship, but it seems likely that an actual poverty impact on maltreatment is at work here.

The third possibility is that our findings are affected by poverty-induced reporting biases. We cannot rule out this possibility because this study is about reported maltreatment incidents rather than all incidents. Many incidents go unreported to CPS in the United States (Sedlak et al., 2010). The estimated poverty-CMR relationship therefore can be subject to reporting biases, such as class bias (i.e., classism toward families in poverty) and class-based visibility bias (i.e., increased visibility of families in poverty due to more frequent contact with social services and thus mandatory reporters). However, prior research suggests that there is little empirical room to support any presence of substantial degrees of poverty-induced reporting biases (Drake et al., 2022; Kim et al., 2018; Pelton, 2015). More research is required to assess the degrees of reporting biases and their potential impacts on possible discrepancies between reported and unreported maltreatment incidents and their relation to poverty.

We found that both White- and Black-specific child poverty coefficients were significant from 2009 to 2018, but also increased during this period. This suggests that the county poverty rate is a strong risk factor for both White and Black CMR rates and that it is more so in more recent years. The increasing trend was somewhat more prominent for the Black-specific coefficient. Trends aside, the generally higher child poverty coefficients for White children are entirely consistent with prior research, suggesting a stronger poverty-CMR relationship among White children than among Black children (Drake et al., 2021). The idea of *differential assortment* (Drake et al., 2009) offers a possible explanation for this tendency. According to this idea, falling into poverty is more difficult for White families than Black families because of historic and present structural advantages for the White population. Those White families who do fall into poverty despite such favored circumstances may have more risk factors (e.g., substance abuse) that can elevate risks of both financial insecurity and child maltreatment.

The Latino-specific poverty-CMR relationship was also all significant from 2009 to 2018. However, the relationship showed little change over time. Prior research has found that the poverty-CMR relationship was far weaker for Latino children than White children (Kim & Drake, 2018; Putnam-Hornstein et al., 2013). This trend is consistent with the notion of a *Latino paradox*, which suggests that Latino families may possess unique cultural protective factors, such as familism, religiosity, and social support, that make it less likely poverty will be associated with child maltreatment (Kim & Drake, 2018; Putnam-Hornstein et al., 2013).

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

With regard to maltreatment type, prior research has found that poverty is most strongly related to neglect, is weaker for physical abuse, and weakest for sexual abuse (Drake et al., 2022; Drake & Pandey, 1996; Kim & Drake, 2018). Correspondingly, whatever factors cause the longitudinal increase in the poverty-CMR relationship, it may be not surprising that such factors increase the relationship the most for neglect, less for physical abuse, and not for sexual abuse. Given the general lack of data and theory in this area, further studies are warranted.

## Strengths and Limitations

This study's use of the national administrative records is a clear strength. This allowed us to construct county-level data across all 50 states and DC, which increases generalizability. It also allowed us to construct longitudinal data over a decade, a period of significant economic change, further supporting future generalizability. This study has several limitations. Our study's outcome of interest is CMRs (screened-in reports) rather than all incidents. Caution is needed in generalizing this study's findings to unreported incidents. Second, this study was done at the county, rather than the individual level, and future research should seek to confirm our findings at the individual level. Counties may be too large to be considered as homogeneous communities as we discussed above. While emerging studies suggest the usefulness of county-level data for an ecological understanding of child maltreatment (Eckenrode et al., 2014; Kim & Drake, 2018; Smith et al., 2021; Zhang et al., 2021), confirmatory work at smaller scales, such as tract and zip codes, are warranted. Third, we used ACS 5-year estimates, which smoothed annual fluctuations in child poverty rates by nearby years' data, conferring advantages and disadvantages as discussed above. Finally, while this study's overall analysis on total CMR rates covered all racial/ethnic children and all maltreatment types, we could not conduct subgroup-specific analysis on some important subcategories of race/ethnicity and maltreatment type (e.g., Native American children and psychological abuse). In most cases, this was because cases in such sub-categories were too few to provide reliable CMR rates for most counties. For psychological abuse, this was because the between-state variation was too large due to the inconsistency in documenting psychological abuse cases between states. Further research is needed specific to these subgroups.

## Implications

Despite the limitations, this study has several important implications. We contribute to the existing knowledge base by identifying for the first time a longitudinal increase of the poverty-CMR relationship, using national population-level data. This study also lays a foundation for further research on mechanisms underlying this longitudinal change and whether this change is also observed in the relationships between broader socioeconomic conditions and child maltreatment indicators. Together, this line of work will help elaborate and specify the current ecological framework of child maltreatment.

We find implications for research design and interpretation. In future studies, especially longitudinal studies, our findings suggest the importance of considering a moderating effect of time on the relationships between poverty and CMR, as well as possibly between other socioeconomic and child maltreatment indicators. An unexpected knowledge gain in this

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

study is that it provides a possible answer for a vexing conundrum for child welfare researchers: why the longitudinal trend of the national CMR rate often does not conform to national poverty rates (Millett et al., 2011). For example, in the 2010s, the national CMR rate increased over time, whereas the national poverty rate decreased. Our findings suggest that the growth of the county-level poverty-CMR relationship dragged up the national CMR rate even while the national poverty rate declined. Readers interpreting prior research and comparing it to current or future work should also be aware that stronger relationships between poverty and maltreatment in more recent work may not be a research artifact, but may show a genuine trend. From an epidemiological perspective, poverty is one of the most important factors in identifying high-risk communities (Daley et al., 2016) and in allocating resources for prevention (Fernandes-Alcantara, 2018). The growing poverty-CMR relationship suggests that it is necessary to place even greater weight on poverty in these considerations.

This study also has policy and practice implications. As we referenced previously, a recent systematic review of the relationship between economic factors and child maltreatment over time (Conrad-Hiebner & Byram, 2020) found four key themes in the empirical literature; that income losses are associated with later maltreatment, that employment buffers maltreatment, that cumulative and housing hardships increase maltreatment and that maternal depression may mediate the poverty-maltreatment relationship. To our minds, those findings suggest that the segregation of child welfare policy from broader economic policies and interventions is problematic. The findings of this paper suggest that this separation is *increasingly* problematic.

We see two core approaches to reducing child maltreatment through economic means. The best approach would be to build policies (such as an expanded EITC) and practices (such as expanded vocational training programs) to reduce the level of economic hardship for families in general. The second approach would be to reorient human services to recognize the core *and expanding* importance of poverty as a fundamental threat to human functioning. A hopeful precedent exists in the recent increased recognition of trauma as a conditioning factor across many human service domains, with “trauma-informed” becoming a byword. As very concrete examples, child welfare services could benefit from increasing material support to the families they serve, either directly (e.g. through emergency fund provision) or indirectly (e.g. through forging relationships with community agencies addressing economic stress). At the very least, child welfare services should “do no harm”, and make sure that involvement with the child welfare system per se does not impart financial stress, perhaps through parents having to miss time at work or having to pay for needed services themselves.

## Conclusions

Understanding the association between poverty and maltreatment is among the most important frontiers in child maltreatment epidemiology and intervention. This study is among the first to frame the poverty/CMR issue longitudinally, and provides preliminary data suggesting that this relationship may have become stronger during the 2010’s. We very much view this work as preliminary and would invite replication and triangulation, particularly using methods and data different from those employed here.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

## Acknowledgements/Funding:

This work was funded by a grant from the Centers for Disease Control and Prevention (CDC), K01CE003229. The analyses presented in this publication were based on data from the National Child Abuse and Neglect Data System Child Files. These data were provided by the National Data Archive on Child Abuse and Neglect at Cornell University, and have been used with permission. The data were originally collected under the auspices of the Children's Bureau (CB). Funding was provided by the CB. The CDC, the collector of the original data, the funder (CB), NDACAN, Cornell University, and the agents or employees of these institutions bear no responsibility for the analyses or interpretation presented here. The information and opinions expressed reflect solely the opinions of the authors.

## References

Anda RF, Felitti VJ, Bremner JD, Walker JD, Whitfield C, Perry BD, Dube SR, & Giles WH (2006). The enduring effects of abuse and related adverse experiences in childhood: A convergence of evidence from neurobiology and epidemiology. European Archives of Psychiatry and Clinical Neuroscience, 256(3), 174–186. 10.1007/s00406-005-0624-4 [PubMed: 16311898]

Aron SB, McCrowell J, Moon A, Yamano R, Roark DA, Simmons M, Tatanashvili Z, & Drake B (2010). Analyzing the relationship between poverty and child maltreatment investigating the relative performance of four levels of geographic aggregation. Social Work Research, 34(3), 169–179. 10.1093/swr/34.3.169

Berger LM (2004). Income, family structure, and child maltreatment risk. Children and Youth Services Review, 26(8), 725–748. 10.1016/j.childyouth.2004.02.017

Chung Y, & Maguire-Jack K (2020). Understanding Movement into Poverty and Poverty Persistence over Time. Journal of Poverty, 24(3), 241–255. 10.1080/10875549.2019.1692271

Conrad A, Paschall KW, & Johnson V (2019). Persistent economic insecurity and harsh parenting: A latent transition analysis. Children and Youth Services Review, 101, 12–22. 10.1016/j.childyouth.2019.03.036

Conrad-Hiebner A, & Byram E (2020). The temporal impact of economic insecurity on child maltreatment: A systematic review. Trauma, Violence, & Abuse, 21(1), 157–178. 10.1177/1524838018756122

Coulton CJ, Crampton DS, Irwin M, Spilsbury JC, & Korbin JE (2007). How neighborhoods influence child maltreatment: A review of the literature and alternative pathways. Child Abuse & Neglect, 31(11–12), 1117–1142. 10.1016/j.chiabu.2007.03.023 [PubMed: 18023868]

Daley D, Bachmann M, Bachmann BA, Pedigo C, Bui M-T, & Coffman J (2016). Risk terrain modeling predicts child maltreatment. Child Abuse & Neglect, 62, 29–38. 10.1016/j.chiabu.2016.09.014 [PubMed: 27780111]

Drake B (1996). Unraveling "unsubstantiated." Child Maltreatment, 1(3), 261–271. 10.1177/1077559596001003008

Drake B, Jonson-Reid M, & Dvalishvili D (2022). Poverty and child maltreatment. In Krugman RD & Korbin JE (Eds.), Handbook of child maltreatment (pp. 239–257). Springer. 10.1007/978-3-030-82479-2_11

Drake B, Jonson-Reid M, Kim H, Chiang C-J, & Davalishvili D (2021). Disproportionate need as a factor explaining racial disproportionality in the CW system. In Dettlaff AJ (Ed.), Racial Disproportionality and Disparities in the Child Welfare System (pp. 159–176). Springer. 10.1007/978-3-030-54314-3_9



Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

Drake B, Lee SM, & Jonson-Reid M (2009). Race and child maltreatment reporting: Are Blacks overrepresented? Children and Youth Services Review, 31(3), 309–316. 10.1016/j.childyouth.2008.08.004 [PubMed: 28435177]

Drake B, & Pandey S (1996). Understanding the relationship between neighborhood poverty and specific types of child maltreatment. Child Abuse & Neglect, 20(11), 1003–1018. 10.1016/0145-2134(96)00091-9 [PubMed: 8958452]

Eckenrode J, Smith EG, McCarthy ME, & Dineen M (2014). Income Inequality and Child Maltreatment in the United States. PEDIATRICS, 133(3), 454–461. 10.1542/peds.2013-1707 [PubMed: 24515511]

Fernandes-Alcantara AL (2018). Maternal and Infant Early Childhood Home Visiting (MIECHV) program: Background and funding (report R43930). Congressional Research Service.

Freisthler B, Merritt DH, & LaScala EA (2006). Understanding the ecology of child maltreatment: A review of the literature and directions for future research. Child Maltreatment, 11(3), 263–280. 10.1177/1077559506289524 [PubMed: 16816324]

Hussey JM, Marshall JM, English DJ, Knight ED, Lau AS, Dubowitz H, & Kotch JB (2005). Defining maltreatment according to substantiation: Distinction without a difference? Child Abuse and Neglect, 29(5 SPEC. ISS.), 479–492. 10.1016/j.chiabu.2003.12.005 [PubMed: 15970321]

Irwin M (2009). The impact of race and neighborhood on child maltreatment: A multi-level discrete time hazard analysis. Unpublished doctoral dissertation, Case Western Reserve University, Cleveland, OH.

Kim H, & Drake B (2017). Duration in poverty-related programs and number of child maltreatment reports: A multilevel negative binomial study. Child Maltreatment, 22(1), 14–23. 10.1177/1077559516679512 [PubMed: 27920221]

Kim H, & Drake B (2018). Child maltreatment risk as a function of poverty and race/ethnicity in the USA. International Journal of Epidemiology, 47(3), 780–787. 10.1093/ije/dyx280 [PubMed: 29390062]

Kim H, Drake B, & Jonson-Reid M (2018). An examination of class-based visibility bias in national child maltreatment reporting. Children and Youth Services Review, 85, 165–173. 10.1016/j.childyouth.2017.12.019

Kim H, & Maguire-Jack K (2021). Longitudinal changes in child maltreatment reports. American Journal of Orthopsychiatry, 91(5), 635–646. 10.1037/ort0000565 [PubMed: 34138607]

Kim H, Wildeman C, Jonson-Reid M, & Drake B (2017). Lifetime prevalence of investigating child maltreatment among US children. American Journal of Public Health, 107(2), 274–280. 10.2105/AJPH.2016.303545 [PubMed: 27997240]

Kohl PL, Jonson-Reid M, & Drake B (2009). Time to leave substantiation behind: Findings from a national probability study. Child Maltreatment, 14(1), 17–26. 10.1177/1077559508326030 [PubMed: 18971346]

Kuhn M, Schularick M, & Steins UI (2020). Income and wealth inequality in America, 1949–2016. Journal of Political Economy, 128(9), 3469–3519. 10.1086/708815

Leiter J, Myers KA, & Zingraff MT (1994). Substantiated and unsubstantiated cases of child maltreatment: Do their consequences differ? Social Work Research, 18(2), 67–82. 10.1093/swr/18.2.67

Maguire-Jack K (2014). Multilevel investigation into the community context of child maltreatment. Journal of Aggression, Maltreatment & Trauma, 23(3), 229–248. 10.1080/10926771.2014.881950

Maguire-Jack K, & Kim H (2021). Rural differences in child maltreatment reports, reporters, and service responses. Children and Youth Services Review, 120, 105792. 10.1016/j.childyouth.2020.105792

Millett L, Lanier P, & Drake B (2011). Are economic trends associated with child maltreatment? Preliminary results from the recent recession using state level data. Children and Youth Services Review, 33(7), 1280–1287. 10.1016/j.childyouth.2011.03.001

Ovwigho PC, Leavitt KL, & Born CE (2003). Risk factors for child abuse and neglect among former TANF families: Do later leavers experience greater risk? Children and Youth Services Review, 25(1–2), 139–163. 10.1016/S0190-7409(02)00269-4

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript



Pac J, Collyer S, Berger L, O'Brien K, Parker E, Pecora P, Rostad W, Waldfogel J, & Wimer C (2023). The effects of child poverty reductions on child protective services involvement. Social Service Review, 97(1), 43–91. 10.1086/723219

Pelton LH (2015). The continuing role of material factors in child maltreatment and placement. Child Abuse & Neglect, 41, 30–39. 10.1016/j.chiabu.2014.08.001 [PubMed: 25169149]

Putnam-Hornstein E, & Needell B (2011). Predictors of child protective service contact between birth and age five: An examination of California's 2002 birth cohort. Children and Youth Services Review, 33(11), 2400–2407. 10.1016/j.childyouth.2011.07.010

Putnam-Hornstein E, Needell B, King B, & Johnson-Motoyama M (2013). Racial and ethnic disparities: A population-based examination of risk factors for involvement with child protective services. Child Abuse & Neglect, 37(1), 33–46. 10.1016/j.chiabu.2012.08.005 [PubMed: 23317921]

Sedlak AJ, Mettenburg J, Basena M, Petta I, McPherson K, Green A, & Li S (2010). Fourth national incidence study of child abuse and neglect (NIS-4): Report to congress. US Department of Health and Human Services.

Semega J, & Kollar M (2022). U.S. Census Bureau, Current Population Reports, P60–276, Income in the United States: 2021. U.S. Government Publishing Office.

Shrider EA, Kollar M, Chen F, & Semega J (2021). Income and poverty in the United States: 2020. U.S. Census Bureau.

Slack KS, Lee BJ, & Berger LM (2007). Do welfare sanctions increase child protection system involvement? A cautious answer. Social Service Review, 81(2), 207–228. 10.1086/516831

Smith BD, Li Q, Wang K, & Smith AM (2021). A national study of child maltreatment reporting at the county level: Interactions among race/ethnicity, rurality and poverty. Children and Youth Services Review, 122, 105925. 10.1016/j.childyouth.2021.105925

US. Department of Agriculture Economic Research Service. (2020). Rural-Urban Continuum Codes. https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

U.S. Department of Health and Human Services. (2021). Child maltreatment 2019. U.S. Department of Health & Human Services. https://www.acf.hhs.gov/cb/data-research/child-maltreatment

Vaithianathan R, Rouland B, & Putnam-hornstein E (2018). Injury and Mortality Among Children Identified as at High Risk of Maltreatment. Pediatrics, 141(2).

Yang M-Y (2015). The effect of material hardship on child protective service involvement. Child Abuse & Neglect, 41, 113–125. 10.1016/j.chiabu.2014.05.009 [PubMed: 24908518]

Zhang L, Simmel C, & Nepomnyaschy L (2021). Income inequality and child maltreatment rates in US counties, 2009–2018. Child Abuse & Neglect, 105328. 10.1016/j.chiabu.2021.105328

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

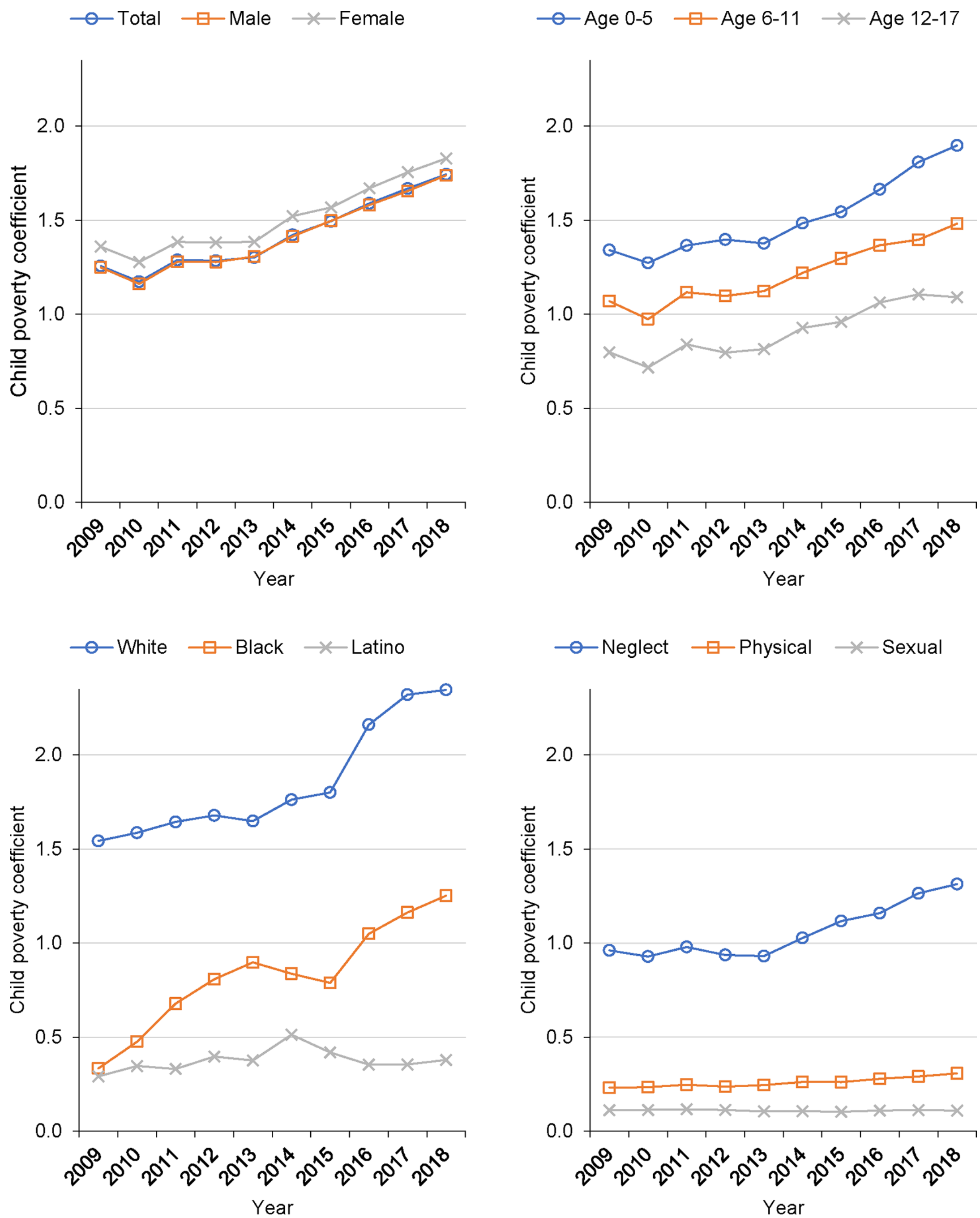


**Figure 1.**

Adjusted coefficients of county child poverty rates on total and subgroup-specific county child maltreatment report rates by year, U.S. counties, 2009–2018.

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

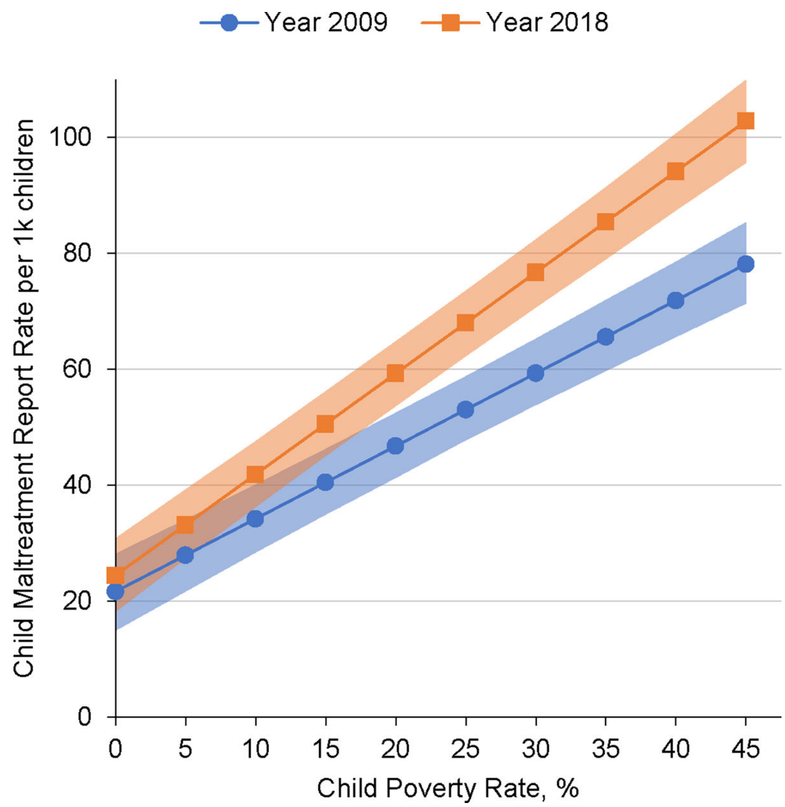


**Figure 2.**

Predicted total child maltreatment report rates by child poverty rates based on the adjusted model, U.S. Counties, 2009 and 2018.

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

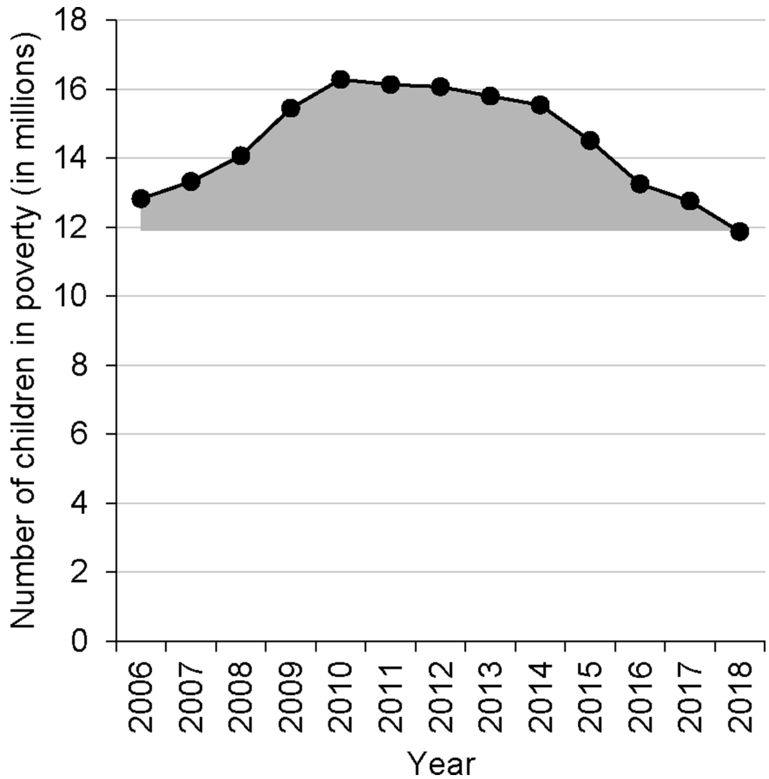


**Figure 3.**

Number of children in poverty, United States, 2006–2018. Source: Table B-5 of Shrider et al. (2021).

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

**Table 1.**

Descriptive Statistics, U.S. Counties, 2009–2018.

| Variable | Mean or % in Each Year | | | | | | | | | | Mean (SD) or % in 2009–2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | |
| **Dependent: Child Maltreatment Report Rate** | | | | | | | | | | | |
| *Total*: # reported per 1k children[a] | 52.9 | 53.9 | 55.1 | 56.0 | 55.2 | 57.1 | 57.4 | 59.5 | 60.8 | 62.1 | 57.1 (27.7) |
| *Age 0–5*: # reported per 1k children aged 0–5[a] | 68.1 | 69.8 | 71.4 | 71.9 | 70.7 | 71.6 | 71.2 | 73.2 | 74.4 | 74.9 | 71.8 (36.2) |
| *Age 6–11*: # reported per 1k children aged 6–11[a] | 52.9 | 53.6 | 55.0 | 56.4 | 56.1 | 58.7 | 59.5 | 61.8 | 63.3 | 65.2 | 58.4 (28.7) |
| *Age 12–17*: # reported per 1k children aged 12–17[a] | 39.5 | 39.9 | 40.6 | 41.3 | 40.7 | 42.8 | 43.2 | 45.2 | 46.5 | 48.1 | 42.9 (21.2) |
| *Male*: # reported per 1k male children[a] | 51.3 | 52.4 | 53.7 | 54.6 | 54.0 | 56.0 | 56.1 | 58.2 | 59.3 | 60.6 | 55.7 (27.1) |
| *Female*: # reported per 1k female children[a] | 53.9 | 54.8 | 56.0 | 56.7 | 55.8 | 57.7 | 57.9 | 59.9 | 61.3 | 62.7 | 57.8 (27.8) |
| *White*: # reported per 1k White children[b] | 45.4 | 46.3 | 47.2 | 48.5 | 47.6 | 48.6 | 48.2 | 50.9 | 51.5 | 53.0 | 48.8 (27.5) |
| *Black*: # reported per 1k Black children[c] | 93.0 | 94.0 | 96.0 | 91.6 | 90.5 | 95.8 | 98.1 | 105.0 | 111.1 | 116.3 | 92.0 (51.0) |
| *Latino*: # reported per 1k Latino children[d] | 39.9 | 40.9 | 40.4 | 40.7 | 40.1 | 42.5 | 42.4 | 45.6 | 47.1 | 48.2 | 41.7 (23.2) |
| *Neglect*: # reported for neglect per 1k children[e] | 37.1 | 38.4 | 39.2 | 38.6 | 38.2 | 38.9 | 39.7 | 40.7 | 42.0 | 42.9 | 39.6 (23.9) |
| *Physical*: # reported for PA per 1k children[f] | 11.8 | 12.4 | 12.6 | 12.6 | 12.4 | 11.9 | 12.7 | 13.6 | 13.8 | 14.1 | 12.4 ( 7.6) |
| *Sexual*: # reported for SA per 1k children[g] | 4.4 | 4.6 | 4.5 | 4.5 | 4.3 | 4.1 | 4.0 | 4.2 | 4.3 | 4.5 | 4.3 ( 2.9) |
| **Independent: Child Poverty Rate** | | | | | | | | | | | |
| *Total*: % children in poverty[a] | 20.1 | 20.9 | 21.7 | 22.3 | 22.2 | 21.6 | 20.7 | 19.9 | 19.0 | 18.0 | 20.6 ( 7.5) |
| *Age 0–5*: % children aged 0–5 in poverty[a] | 23.5 | 24.4 | 25.2 | 25.6 | 25.3 | 24.5 | 23.3 | 22.2 | 21.2 | 19.9 | 23.5 ( 8.6) |
| *Age 6–11*: % children aged 6–11 in poverty[a] | 19.9 | 20.8 | 21.7 | 22.3 | 22.3 | 21.7 | 20.9 | 20.3 | 19.4 | 18.3 | 20.8 ( 7.9) |
| *Age 12–17*: % children aged 12–17 in poverty[a] | 17.1 | 17.8 | 18.5 | 19.2 | 19.1 | 18.7 | 18.0 | 17.4 | 16.7 | 15.9 | 17.8 ( 6.7) |
| *White*: % White children in poverty[b] | 12.9 | 13.6 | 14.2 | 14.5 | 14.4 | 14.0 | 13.3 | 12.8 | 12.2 | 11.6 | 13.3 ( 6.0) |
| *Black*: % Black children in poverty[c] | 35.8 | 37.1 | 38.1 | 37.9 | 37.6 | 37.1 | 35.3 | 33.8 | 32.3 | 31.0 | 36.1 (14.7) |
| *Latino*: % Latino children in poverty[d] | 30.7 | 32.0 | 32.7 | 33.4 | 33.2 | 32.1 | 30.8 | 29.6 | 28.3 | 26.2 | 30.9 (11.1) |
| **Control** [a] | | | | | | | | | | | |
| % Black children among resident children | 12.3 | 12.2 | 12.1 | 13.1 | 13.0 | 13.0 | 13.0 | 12.9 | 12.9 | 12.8 | 12.8 (13.9) |

Author Manuscript
Author Manuscript
Author Manuscript
Author Manuscript

| Variable | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | Mean (SD) or % in 2009–2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean or % in Each Year | | | | | | | | | | |
| % Latino children among resident children | 16.9 | 16.9 | 17.3 | 17.4 | 17.6 | 17.8 | 18.0 | 18.3 | 18.5 | 18.8 | 17.8 (17.0) |
| % foreign-born among residents | 8.5 | 8.4 | 8.5 | 8.5 | 8.6 | 8.6 | 8.7 | 8.7 | 8.8 | 8.8 | 8.6 ( 7.6) |
| % children among residents | 24.0 | 23.7 | 23.5 | 23.4 | 23.2 | 23.0 | 22.8 | 22.7 | 22.5 | 22.4 | 23.1 ( 3.0) |
| % elderly persons (≥ age 65) among residents | 13.4 | 13.7 | 14.0 | 14.2 | 14.6 | 15.1 | 15.5 | 15.9 | 16.3 | 16.7 | 15.0 ( 4.2) |
| % male among adults aged 20–64 years | 49.7 | 49.7 | 49.7 | 49.7 | 49.7 | 49.7 | 49.8 | 49.8 | 49.8 | 49.8 | 49.7 ( 1.5) |
| % children with disabilities among resident children | 12.9 | 12.9 | 13.0 | 13.2 | 13.4 | 13.6 | 13.6 | 13.6 | 13.7 | 13.7 | 13.4 ( 3.1) |
| % moved in one year among persons | 15.9 | 15.7 | 15.6 | 15.6 | 15.5 | 15.4 | 15.2 | 15.1 | 14.8 | 14.4 | 15.3 ( 3.9) |
| Urbanicity: Large urban (1) | 32.0% | 31.9% | 31.8% | 32.6% | 32.5% | 32.5% | 32.7% | 32.7% | 32.7% | 32.7% | 32.4% |
| Urbanicity: Small urban (2 and 3) | 50.1% | 50.1% | 50.2% | 49.2% | 49.1% | 49.1% | 49.3% | 49.3% | 49.3% | 49.3% | 49.5% |
| Urbanicity: Rural (4–9) | 17.9% | 18.0% | 18.0% | 18.2% | 18.3% | 18.3% | 18.0% | 18.0% | 18.0% | 18.0% | 18.1% |

[a] N = 6150.

[b] N = 6152.

[c] N = 5613.

[d] N = 6060.

[e] N = 6151.

[f] N = 6119.

[g] N = 6147.

N = # county-year observations. PA = physical abuse. SA = sexual abuse.

Author Manuscript

**Table 2.**

Unadjusted Coefficients of Child Poverty (CP) Rates on Total and Subgroup-Specific Child Maltreatment Report (CMR) Rates by Year, U.S. Counties, 2009–2018.

| | Total CMR | Age-Specific CMR | | | Sex-Specific CMR | | Race/Ethnicity-Specific CMR | | | Type-Specific CMR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Age 0–5 | Age 6–11 | Age 12–17 | Male | Female | White | Black | Latino | Neglect | Physical Abuse | Sexual Abuse |
| **Main & Interaction Terms** | | | | | | | | | | | | |
| "CP" main (reference year 2009) | 1.11** | 1.41** | 1.01** | 0.76** | 1.06** | 1.15** | 2.24** | 0.49** | 0.35** | 0.82** | 0.22** | 0.10** |
| "CP × Year 2010" interaction | −0.09 | −0.08 | −0.10 | −0.09 | −0.09 | −0.09 | 0.03 | 0.11 | 0.05 | −0.03 | 0.00 | 0.00 |
| "CP × Year 2011" interaction | 0.05 | 0.04 | 0.06 | 0.04 | 0.05 | 0.04 | 0.06 | 0.29* | 0.01 | 0.03 | 0.02 | 0.01 |
| "CP × Year 2012" interaction | 0.06 | 0.06 | 0.05 | 0.02 | 0.06 | 0.05 | 0.09 | 0.44** | 0.06 | 0.00 | 0.01 | 0.00 |
| "CP × Year 2013" interaction | 0.08 | 0.04 | 0.08 | 0.05 | 0.10 | 0.06 | 0.05 | 0.52** | 0.06 | 0.00 | 0.02 | 0.00 |
| "CP × Year 2014" interaction | 0.20 | 0.14 | 0.17 | 0.16 | 0.20 | 0.18 | 0.18 | 0.44** | 0.21** | 0.09 | 0.04 | 0.00 |
| "CP × Year 2015" interaction | 0.27** | 0.20 | 0.25* | 0.20* | 0.28** | 0.23* | 0.21 | 0.39** | 0.13 | 0.18 | 0.04 | −0.01 |
| "CP × Year 2016" interaction | 0.37** | 0.34** | 0.32** | 0.32** | 0.37** | 0.34** | 0.59** | 0.66** | 0.08 | 0.24** | 0.05 | 0.00 |
| "CP × Year 2017" interaction | 0.49** | 0.55** | 0.39** | 0.38** | 0.48** | 0.46** | 0.78** | 0.74** | 0.12 | 0.37** | 0.07* | 0.01 |
| "CP × Year 2018" interaction | 0.56** | 0.62** | 0.46** | 0.38** | 0.55** | 0.54** | 0.77** | 0.88** | 0.13 | 0.42** | 0.09** | 0.00 |
| **Year-Specific CP Coefficient (= main + interaction terms)** | | | | | | | | | | | | |
| CP coefficient in 2009 | 1.11** | 1.41** | 1.01** | 0.76** | 1.06** | 1.15** | 2.24** | 0.49** | 0.35** | 0.82** | 0.22** | 0.10** |
| CP coefficient in 2010 | 1.02** | 1.33** | 0.92** | 0.68** | 0.98** | 1.07** | 2.27** | 0.59** | 0.40** | 0.78** | 0.23** | 0.10** |
| CP coefficient in 2011 | 1.16** | 1.45** | 1.07** | 0.80** | 1.11** | 1.19** | 2.30** | 0.77**a | 0.36** | 0.85** | 0.24** | 0.11** |
| CP coefficient in 2012 | 1.17** | 1.47** | 1.06** | 0.78** | 1.12** | 1.20** | 2.33** | 0.93**b | 0.41** | 0.82** | 0.23** | 0.10** |
| CP coefficient in 2013 | 1.19** | 1.45** | 1.09** | 0.81** | 1.16** | 1.21** | 2.29** | 1.01**b | 0.41** | 0.82** | 0.24** | 0.10** |
| CP coefficient in 2014 | 1.31** | 1.55** | 1.18** | 0.93** | 1.26** | 1.34** | 2.42** | 0.92**b | 0.56**b | 0.91** | 0.26** | 0.10** |
| CP coefficient in 2015 | 1.38**b | 1.61** | 1.26**a | 0.97**a | 1.34**b | 1.38**a | 2.45** | 0.88**b | 0.48** | 1.00** | 0.26** | 0.09** |
| CP coefficient in 2016 | 1.48**b | 1.75**b | 1.34**b | 1.08**b | 1.43**b | 1.49**b | 2.83**b | 1.15**b | 0.43** | 1.05**b | 0.28** | 0.10** |
| CP coefficient in 2017 | 1.60**b | 1.95**b | 1.40**b | 1.14**b | 1.54**b | 1.61**b | 3.02**b | 1.23**b | 0.47** | 1.19**b | 0.30**a | 0.11** |

Author Manuscript

| | Total CMR | Age-Specific CMR | | | Sex-Specific CMR | | Race/Ethnicity-Specific CMR | | | Type-Specific CMR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Age 0–5 | Age 6–11 | Age 12–17 | Male | Female | White | Black | Latino | Neglect | Physical Abuse | Sexual Abuse |
| CP coefficient in 2018 | 1.67 **b | 2.02 **b | 1.48 **b | 1.14 **b | 1.61 **b | 1.69 **b | 3.01 **b | 1.36 **b | 0.48 ** | 1.24 **b | 0.31 **b | 0.10 ** |

Note: The main and interaction terms are estimated by linear multilevel modeling. The CP coefficient in 2009 is the CP main term. The CP coefficient in 2017 (1.60) is, for example, the sum of the CP main term (1.11) and the "CP × Year 2017" interaction term (0.49).

* p<.10

** p<.05

[a] The CP coefficient in the given year is marginally significantly (p<.10) different from the CP coefficient in 2009.

[b] The CP coefficient in the given year is significantly (p<.05) different from the CP coefficient in 2009.

Author Manuscript Author Manuscript Author Manuscript Author Manuscript

**Table 3.**

Adjusted Coefficients of Child Poverty (CP) Rates on Total and Subgroup-Specific Child Maltreatment Report (CMR) Rates by Year, U.S. Counties, 2009–2018.

| | | Age-Specific CMR | | | Sex-Specific CMR | | Race/Ethnicity-Specific CMR | | | Type-Specific CMR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Total CMR | Age 0–5 | Age 6–11 | Age 12–17 | Male | Female | White | Black | Latino | Neglect | Physical Abuse | Sexual Abuse |
| **Main and Interaction Terms** | | | | | | | | | | | | |
| "CP" main (reference year 2009) | 1.26$^{**}$ | 1.34$^{**}$ | 1.07$^{**}$ | 0.80$^{**}$ | 1.25$^{**}$ | 1.36$^{**}$ | 1.54$^{**}$ | 0.33$^{**}$ | 0.29$^{**}$ | 0.96$^{**}$ | 0.23$^{**}$ | 0.11$^{**}$ |
| "CP × Year 2010" interaction | −0.08 | −0.07 | −0.10 | −0.08 | −0.09 | −0.08 | 0.04 | 0.14 | 0.05 | −0.03 | 0.00 | 0.00 |
| "CP × Year 2011" interaction | 0.03 | 0.02 | 0.05 | 0.04 | 0.03 | 0.02 | 0.10 | 0.34$^{**}$ | 0.04 | 0.02 | 0.02 | 0.00 |
| "CP × Year 2012" interaction | 0.03 | 0.06 | 0.03 | 0.00 | 0.03 | 0.02 | 0.14 | 0.47$^{**}$ | 0.11 | −0.02 | 0.00 | 0.00 |
| "CP × Year 2013" interaction | 0.05 | 0.04 | 0.05 | 0.02 | 0.06 | 0.03 | 0.11 | 0.56$^{**}$ | 0.08 | −0.03 | 0.01 | −0.01 |
| "CP × Year 2014" interaction | 0.17 | 0.14 | 0.15 | 0.13 | 0.16 | 0.16 | 0.22$^{*}$ | 0.50$^{**}$ | 0.22$^{**}$ | 0.07 | 0.03 | −0.01 |
| "CP × Year 2015" interaction | 0.24$^{**}$ | 0.20 | 0.23$^{**}$ | 0.16 | 0.25$^{**}$ | 0.21$^{*}$ | 0.26$^{*}$ | 0.45$^{**}$ | 0.13 | 0.16$^{*}$ | 0.03 | −0.01 |
| "CP × Year 2016" interaction | 0.33$^{**}$ | 0.32$^{**}$ | 0.30$^{**}$ | 0.26$^{**}$ | 0.33$^{**}$ | 0.31$^{**}$ | 0.62$^{**}$ | 0.72$^{**}$ | 0.06 | 0.20$^{**}$ | 0.05 | 0.00 |
| "CP × Year 2017" interaction | 0.41$^{**}$ | 0.47$^{**}$ | 0.33$^{**}$ | 0.31$^{**}$ | 0.41$^{**}$ | 0.40$^{**}$ | 0.78$^{**}$ | 0.83$^{**}$ | 0.06 | 0.30$^{**}$ | 0.06 | 0.00 |
| "CP × Year 2018" interaction | 0.49$^{**}$ | 0.56$^{**}$ | 0.41$^{**}$ | 0.29$^{**}$ | 0.49$^{**}$ | 0.47$^{**}$ | 0.80$^{**}$ | 0.92$^{**}$ | 0.09 | 0.35$^{**}$ | 0.08$^{**}$ | 0.00 |
| **Year-Specific CP Coefficient (= main + interaction terms)** | | | | | | | | | | | | |
| CP coefficient in 2009 | 1.26$^{**}$ | 1.34$^{**}$ | 1.07$^{**}$ | 0.80$^{**}$ | 1.25$^{**}$ | 1.36$^{**}$ | 1.54$^{**}$ | 0.33$^{**}$ | 0.29$^{**}$ | 0.96$^{**}$ | 0.23$^{**}$ | 0.11$^{**}$ |
| CP coefficient in 2010 | 1.17$^{**}$ | 1.27$^{**}$ | 0.97$^{**}$ | 0.72$^{**}$ | 1.16$^{**}$ | 1.28$^{**}$ | 1.59$^{**}$ | 0.48$^{**}$ | 0.35$^{**}$ | 0.93$^{**}$ | 0.23$^{**}$ | 0.11$^{**}$ |
| CP coefficient in 2011 | 1.29$^{**}$ | 1.37$^{**}$ | 1.12$^{**}$ | 0.84$^{**}$ | 1.28$^{**}$ | 1.38$^{**}$ | 1.64$^{**}$ | 0.68$^{**b}$ | 0.33$^{**}$ | 0.98$^{**}$ | 0.25$^{**}$ | 0.12$^{**}$ |
| CP coefficient in 2012 | 1.28$^{**}$ | 1.40$^{**}$ | 1.10$^{**}$ | 0.80$^{**}$ | 1.28$^{**}$ | 1.38$^{**}$ | 1.68$^{**}$ | 0.81$^{**b}$ | 0.40$^{**}$ | 0.94$^{**}$ | 0.24$^{**}$ | 0.11$^{**}$ |
| CP coefficient in 2013 | 1.30$^{**}$ | 1.38$^{**}$ | 1.12$^{**}$ | 0.81$^{**}$ | 1.31$^{**}$ | 1.38$^{**}$ | 1.65$^{**}$ | 0.90$^{**b}$ | 0.38$^{**}$ | 0.93$^{**}$ | 0.24$^{**}$ | 0.10$^{**}$ |
| CP coefficient in 2014 | 1.42$^{**}$ | 1.48$^{**}$ | 1.22$^{**}$ | 0.93$^{**}$ | 1.41$^{**}$ | 1.52$^{**}$ | 1.76$^{**a}$ | 0.84$^{**b}$ | 0.51$^{**b}$ | 1.03$^{**}$ | 0.26$^{**}$ | 0.11$^{**}$ |
| CP coefficient in 2015 | 1.49$^{**b}$ | 1.54$^{**}$ | 1.30$^{**b}$ | 0.96$^{**}$ | 1.50$^{**b}$ | 1.57$^{**a}$ | 1.80$^{**a}$ | 0.79$^{**b}$ | 0.42$^{**}$ | 1.12$^{**a}$ | 0.26$^{**}$ | 0.10$^{**}$ |
| CP coefficient in 2016 | 1.59$^{**b}$ | 1.66$^{**b}$ | 1.37$^{**b}$ | 1.06$^{**b}$ | 1.58$^{**b}$ | 1.67$^{**b}$ | 2.16$^{**b}$ | 1.05$^{**b}$ | 0.35$^{**}$ | 1.16$^{**b}$ | 0.28$^{**}$ | 0.11$^{**}$ |
| CP coefficient in 2017 | 1.67$^{**b}$ | 1.81$^{**b}$ | 1.40$^{**b}$ | 1.10$^{**b}$ | 1.65$^{**b}$ | 1.75$^{**b}$ | 2.32$^{**b}$ | 1.16$^{**b}$ | 0.35$^{**}$ | 1.26$^{**b}$ | 0.29$^{**}$ | 0.11$^{**}$ |

| | Total CMR | Age-Specific CMR | | | Sex-Specific CMR | | Race/Ethnicity-Specific CMR | | | Type-Specific CMR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Age 0–5 | Age 6–11 | Age 12–17 | Male | Female | White | Black | Latino | Neglect | Physical Abuse | Sexual Abuse |
| CP coefficient in 2018 | 1.74**b | 1.90**b | 1.48**b | 1.09**b | 1.74**b | 1.83**b | 2.35**b | 1.25**b | 0.38** | 1.31**b | 0.31**b | 0.11** |

Note: The main and interaction terms are estimated by linear multilevel modeling, while adjusting for % Black children among resident children, % Latino children among resident children, % foreign-born among residents, % children among residents, % elderly persons (≥ age 65) among residents, % male among adults aged 20–64, % children with disabilities, % moved in one year, and urbanicity. The CP coefficient in 2009 is the CP main term. The CP coefficient in 2017 (1.67) is, for example, the sum of the CP main term (1.26) and the “CP × Year 2017” interaction term (0.41).

[*] p<.10

[**] p<.05

[a] The CP coefficient in the given year is marginally significantly (p<.10) different from the CP coefficient in 2009.

[b] The CP coefficient in the given year is significantly (p<.05) different from the CP coefficient in 2009.



Author Manuscript Author Manuscript Author Manuscript Author Manuscript