Published in final edited form as:
J Interpers Violence. 2023 January ; 38(1-2): NP262–NP287. doi:10.1177/08862605221080148.

Community Food Insecurity and Child Maltreatment Reports: County-Level Analysis of U.S. National Data from 2009 to 2018

Hyunil Kim[1,*], **Craig Gundersen**[2], **Liliane Windsor**[1]

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

[2]Baylor University, Waco, Texas

Abstract

Current literature suggests that food insecurity increases child maltreatment risk. Yet, existing evidence is limited to individual-level associations among low-income, high-risk populations based on local, mostly urban data. This study aims to generalize prior findings to community-level associations in general populations, using national data including all urban-rural areas. We examined, for the first time, if food insecurity rates increase child maltreatment report (CMR) rates at the county level after controlling for potential confounders. We examined both within-community longitudinal changes (i.e., within-effects) and inter-community differences (i.e., between-effects) of food insecurity rates and their associations with CMR rates. We also examined differences by age, sex, race/ethnicity, maltreatment type, and urbanicity. We constructed longitudinal county-level data by linking multiple national databases, including all substantiated and unsubstantiated CMR records, the Map the Meal Gap's community food insecurity estimates, and Census data. The data covered over 96% of U.S. counties from 2009-2018. For analysis, we used within-between random effects models. Regarding between-effects, we found that in inter-community comparisons, higher food insecurity rates were significantly associated with increased CMR rates. This association was consistent by age, sex, maltreatment type, and urbanicity. For within-effects, we found that the association between longitudinal changes of food insecurity rates and CMR rates significantly differed by urbanicity. Specifically, longitudinal increases of food insecurity rates significantly increased CMR rates among large urban counties, but not among small urban and rural counties. Study findings highlight the importance of conducting further research to better understand the mechanisms through which food insecurity impact child maltreatment at both individual and community levels. Our community-level findings from general populations especially have significant implications for community-based programs and large-scale policies to achieve population-level impact on child well-being.

Introduction

While the strong association between income poverty and child maltreatment has been well established (Drake & Jonson-Reid, 2014; Pelton, 2015), evidence regarding food insecurity is sparse. Some studies suggest that material hardships (e.g., food insecurity)

*Corresponding Author: Hyunil Kim (hyunil@illinois.edu; T. 217-300-8122; address: 1010 W Nevada St, Urbana, IL 61801).
Financial Disclosure/Conflict of Interest: None

more accurately represent physical and psychological aspects of financial difficulties, compared with income poverty, and mounting evidence supports the associations between various material hardships and child maltreatment (Conrad-Hiebner & Byram, 2020). While food is one of the most important basic needs, prior research is limited to individual-level associations among low-income, high-risk populations based on local, mostly urban data (e.g., Helton et al., 2019). From a public health perspective, further evidence is needed that can serve as empirical grounds for community-based programs and large-scale policies for general populations. The current study addresses this need through examining county-level associations between food insecurity and child maltreatment reports among the general population in the U.S., using national data.

Background

Food insecurity "exists whenever the availability of nutritionally adequate and safe foods or the ability to acquire acceptable foods in socially acceptable ways is limited or uncertain" (National Research Council, 2006, p. 4). The Core Food Security Module (CFSM) is the standard national measure of food insecurity (Bickel et al., 2000). CFSM was published in 1997 and revised in 2000 by the U.S. Department of Agriculture (USDA) and since then has provided reliable counts of food insecurity and hunger in the U.S. (Bickel et al., 2000). CFSM is one of the most rigorously evaluated food insecurity instruments and has been found to have good reliability and validity (Marques et al., 2015). CFSM consists of 18 questions, and households are considered to be food insecure when reporting three or more food insecure conditions out of the first 10 questions for households without children and all the 18 questions for household with children (Coleman-Jensen et al., 2020). According to CFSM measures, 10.5% (13.7 million) of U.S. households experienced food insecurity in 2019 (Coleman-Jensen et al., 2020). The prevalence among households with children was slightly higher, 13.6% (Coleman-Jensen et al., 2020). In general, caregivers ensure children meet their nutritional needs even if adult household members are food insecure. But this puts extra distress on caregivers and may impair caregiver functioning. Prior studies found that household food insecurity was associated with a wide range of negative child outcomes in developmental, cognitive, language, health, motor, social, emotional, and behavioral domains even in high-income countries (Gundersen & Ziliak, 2015; Oliveira et al., 2020; Shankar et al., 2017).

Prior Findings on Food Insecurity and Child Maltreatment

Food insecurity is associated with increased risks of experiencing an investigated neglect report, a substantiated child maltreatment report, self-reported abuse and neglect, and parent-to-child aggression (Epstein, 2001; Helton et al., 2019; Mersky & Janczewski, 2018; Slack et al., 2011; Yang, 2015). However, important knowledge gaps still exist. First, prior studies were mostly based on low-income or high-risk populations. It is unknown how this relationship manifests in general populations. Second, prior data were further limited to local and mostly urban data. Ecological contexts of child maltreatment can be very different between urban and rural areas (Maguire-Jack & Kim, 2021), suggesting associations with food insecurity may differ. Finally, to our knowledge, no study has examined a community-level association between food insecurity and child maltreatment. From a public health standpoint, such associations in general populations can inform community-based programs and large-scale policies (Covington, 2013).

Theoretical Frameworks that Explain the Relationship between Food Insecurity and Child Maltreatment

The existing literature on child maltreatment and economic hardships suggests several pathways from food insecurity to child maltreatment. While the current study does not examine pathways, we review several of these in this section in order to explain why a community-level relationship between food insecurity and child maltreatment is possible. We review both individual-level and community-level pathways since both pathways might generate a community-level relationship. High food insecure communities may have high child maltreatment rates simply because certain communities have many food insecure families with high child maltreatment risk. A community-level relationship is also possible due to contextual effects of concentrating food insecurity in certain communities.

Perhaps the most popular explanation of individual-level pathways is the family stress model (Conger et al., 1992; Conrad-Hiebner & Byram, 2020; Helton et al., 2019). The model proposes that being food insecure and prioritizing food and other basic necessities due to food insecurity may create economic pressure to meet basic needs (Knowles et al., 2016). This pressure can provoke family chaos and disrupt daily living, leading to increased parental distress, which in turn can deteriorate the relationships between family members (Conger et al., 1992; Fiese et al., 2016). Interparental conflicts may increase a child’s risk of exposure to domestic violence (i.e., neglect) and/or experiencing physical abuse due to domestic violence (Jackson et al., 2018). Parent-child conflicts may increase the risk of harsh parenting and parent-to-child aggression and then escalate into physical abuse (Helton et al., 2019). Under high stress, even trivial irritations by children can arouse anger from parents, which may increase physical abuse risk (Pelton, 2015). High parental stress can also lead to parental depression, which may dissociate parents from their caregiver role and increase neglect risk (Pelton, 2015).

Evidence supports associations between food insecurity and parental physical, mental, and behavioral issues (Gundersen & Ziliak, 2015; Helton et al., 2019; Jackson et al., 2018). While parental stress may mediate these associations as the family stress model posits, other individual-level pathways are also entirely possible. For example, some researchers suggest that vitamin deficiency can deteriorate psychological and behavioral functioning of parents (e.g., depression, anxiety, and diminished reaction; Heflin et al., 2005). Others suggest that nutrient deficiency may degrade parental brain functioning that involve behavioral inhibition such as impulse control (Helton et al., 2019). Behavioral models also suggest that withdrawal or omission of food can provoke aggression among some species (Baum & Kupfer, 2005). Food insecurity may link to parental physical, mental, and behavioral issues directly and, in turn, may increase child maltreatment risk (Stith et al., 2009).

Even without deteriorating parental well-being and functioning, food insecurity may increase child maltreatment risk. Families with limited food resources and options may have heavy burdens of resource management to prioritize their needs of food and other basic necessities (e.g., shelter, clothing, education, and health care; Knowles et al., 2016), which may simply decrease a chance to meet children's basic needs. Failure to provide for children's basic needs due solely to economic reasons generally does not constitute neglect in state laws (Child Welfare Information Gateway, 2019), and economic difficulties do not always result in failure to provide. However, food insecurity and trade-offs between food and other basic needs may greatly limit resources and options of families to meet their children's basic needs and increase burdens of resource management. Compared to food secure families, food insecure families have to be more vigilant to prevent neglect.

Food insecurity may increase the risk of poor child outcomes, which in turn may increase the burden of parenting and then child maltreatment risk. Prior studies suggest that food insecurity is linked to poor cognitive, social, emotional, behavioral, and health outcomes of children (Gundersen & Ziliak, 2015; Oliveira et al., 2020; Shankar et al., 2017). High caregiver burdens due to these issues may increase child maltreatment risk (Stith et al., 2009).

While theoretical work for the community-level pathways from food insecurity to child maltreatment is sparse, general theories for community contextual effects are applicable. The sociological approach suggests that concentrated disadvantages (e.g., poverty and food insecurity) may deteriorate favorable neighborhood processes such as social organization and collective efficacy and in turn may impede collective engagement to alleviate community problems (e.g., child maltreatment; Sampson et al., 1999). The psychological approach, on the other hand, considers concentrated disadvantages as environmental stressors, which can increase child maltreatment risk especially among families who lack social supports to buffer such stressors (Belsky, 1993). Finally, the economic approach proposes that concentrated disadvantages may reduce community resources available to residents and accordingly increase their risk of child maltreatment (Drake & Jonson-Reid, 2014). For example, concentration of food insecure families may rapidly deplete community food resources (e.g., food pantries), which may increase the hardships of already financially distressed families.

Current Study

The current study examined county-level associations between food insecurity rates and child maltreatment report (CMR) rates, using national data. We examined how within-county longitudinal changes of food insecurity rates (i.e., within-effects of food insecurity rates, WFI) are associated with CMR rates. That is, we examined whether, when a county's annual food insecurity rate increases over time, the county's annual CMR rate also increases. We also examined how inter-county differences of food insecurity rates (i.e., between-effects of food insecurity rates, BFI) are associated with CMR rates. That is, we examined whether counties with higher food insecurity rates have higher CMR rates when comparing multiple counties cross-sectionally. We examined both within-effects and between-effects simultaneously in modeling. This approach is a notable strength to have a comprehensive examination of a community condition (e.g., community food insecurity) because a community condition not only can differ in a cross-sectional spectrum of social contexts across multiple communities, but also can be subject to change longitudinally when following up with a community over a period of time. In line with the increasing attention to urban-rural differences in child welfare research (Maguire-Jack & Kim, 2021), we examined whether these associations differ by urbanicity (i.e., interactions between food insecurity and urbanicity). These associations and interactions were examined for total, age-specific, gender-specific, race/ethnicity-specific, and maltreatment type-specific CMR rates.

Methods

Data and Sample

Linking multiple national databases at the county level from 2009-2018, including CMR data (for dependent variables), food insecurity data (for independent variables), and Census data (for control variables) produced the longitudinal ecological data set. While food insecurity and Census data were provided at the county level, maltreatment data were individual-level data and needed to be aggregated by county. This section reports how we managed/aggregated CMR data and prepared the longitudinal county-level data for analysis.

Official CMR case/child-level records on all children reported to the child protective services (CPS) agencies for child maltreatment in the 50 states and DC were obtained from the National Child Abuse and Neglect Data System (NCANDS) Child Files. Among all records, we excluded duplicate records (0.06%), fatal cases (0.03%), child age > 17 cases (0.12%), unborn child cases (0.11%), missing child age cases (0.52%), and missing county identifier cases (0.29%). We further excluded records of Georgia 2009-2011, Pennsylvania 2009-2014, and Tennessee 2009 (1.21%) due to county identifier entry errors (i.e., most cases in these state-years were assigned with the suppressed county identifier “000”). These exclusions amounted 2.34% of CMR records. The final child-level data included 31,702,456 reported children from 2009-2018 based on annual unique counts (i.e., a child counted once per year). Our inclusion of both substantiated and unsubstantiated CMRs reflects strong evidence that substantiation decisions are unreliable and that rates based on only substantiated CMRs are vast underestimates of child maltreatment rates (Drake, 1996; Hussey et al., 2005; Kohl et al., 2009).

We aggregated the child-level CMR data into counties (precisely, county-year observations) to compute county CMR rate—i.e., the number of reported children per 1,000 children each year. Among 32,215 county-year observations from 2009 to 2018 (= about 3,222 counties × 10 years), we excluded the following records: 185 county-year observations due to no data submission to NCANDS Child Files (all ND counties in 2009, all OR counties in 2009-2011, and two MA counties in 2009-2018) and 984 county-year observations due to suspected entry errors of county identifiers (all GA counties in 2009-2011, all PA counties in 2009-2014, and all TN counties in 2009). Altogether, the final county-level covered 96.37% of U.S. counties from 2009 to 2018.

During the county-level aggregation, we combined many low-populated counties into one *pseudo* county per state. NCANDS Child Files provide 2-digit state and 3-digit county Federal Information Processing System (FIPS) codes, which indicate the geographic locations of CMRs. NCANDS suppressed the 3-digit county FIPS for records from counties with fewer than 1,000 CMRs by replacing the original county FIPS codes with “000”, while state FIPS codes were still available for these records. We combined these suppressed counties into one *pseudo* county area per state, using state FIPS codes. This aggregation excluded no data and provided more reliable counts of reported children in low-populated counties. However, it obscured within-state variation between many low-populated counties. In the final data, 5,697 county-year observations were identified (i.e., having an original County FIPS) while 25,349 county-year observations were suppressed (i.e., having the county FIPS "000"). The latter were combined into 456 *pseudo* county-year observations. The final data included 6,153 county-year observations (= 5,697 identified county-years + 456 *pseudo* county-years), nested in 639 counties (and *pseudo* counties) and in 51 states (50 states and DC).

We obtained county-level food insecurity data from the Map the Meal Gap (MMG) study and data for control variables from the American Community Surveys (ACS). To create the county-level longitudinal data for analysis we aggregated these data into *pseudo* counties in the same manner of child maltreatment data.

Measures

We computed county-level CMR rates (= number of reported children per 1,000 children) overall and within subcategories of child age, gender, and race/ethnicity, and maltreatment subtype (see Table 1). Altogether, we measured 12 dependent variables and estimated models for each of these variables.

We obtained county-level food insecurity rates (= percentages of persons in a food insecure household) from the MMG study (Feeding America, 2021). MMG has generated county-level food insecurity data through a two-step process. First, MMG estimated a state-level model of food insecurity rates (measured by CFSM) based on the following predictors from the Current Population Surveys: poverty rates (excluding college students), unemployment rates, median income, homeowner rates, disability rates, % Black, and % Latino. Second, MMG estimated county food insecurity rates by applying the state-level food security model to county-level predictors from the ACS. The MMG-estimated county food insecurity rates showed high consistency with some available direct measures (Gundersen et al., 2014). MMG has provided food insecurity rates for all U.S. counties since 2009.

For urbanicity, we used the 2013 USDA Rural-Urban Continuum Codes. We collapsed the original nine categories into three (i.e., large urban, small urban, and rural; see Table 1).

Control variables were selected based on prior research on community-level risk/protective factors, such as socioeconomic, demographic, child care burden, and residential instability (Coulton et al., 2007). We used the following control variables, which were available in the ACS data: child poverty rates, median owner-occupied house values, percentages of children among county residents, percentages of male among county adults aged 20-64 years, percentages of county residents who moved within a year, and percentages of foreign-born among county residents (see Table 1). The variables that were used to estimate county food insecurity rates by MMG were excluded from control variables to avoid multicollinearity. One exception was child poverty rates, which we used in some models with caution of moderate multicollinearity (VIF > 5) to examine independence of food insecurity rates from child poverty rates in their associations with CMR rates.

Analysis

We used within-between random effects (REWB) models to examine how longitudinal changes of county food insecurity rates (i.e., WFI) and inter-county differences in food insecurity rates (i.e., BFI) were associated with county CMR rates. The basic statistical model is:

$$\begin{aligned} Y_{tij} = \beta_0 + \beta_1\left(FI_{tij} - \overline{FI}_{ij}\right) + \beta_2\overline{FI}_{ij} + \beta_3 Urban_{ij} + \beta_4\left(x_{tij} - \overline{x}_{ij}\right) + \beta_5\overline{x}_{ij} + \beta_6 Year_{ij} + V_{0j} \\ + V_{1j}\left(FI_{tij} - \overline{FI}_{ij}\right) + V_{2j}\overline{FI}_{ij} + U_{0ij} + U_{1ij}\left(FI_{tij} - \overline{FI}_{ij}\right) + R_{tij} \end{aligned}$$

Here, Y_{tij} is the CMR rate for the tth county-year in the ith county in the jth state. FI_{tij} is the food insecurity rate for the tth county-year in the ith county in the jth state. $\overline{FI}_{ij}$ is the mean of the food insecurity rates from 2009-2018 for the ith county in the jth state. $Urban_{ij}$ is the vector of urbanicity categories (large urban and small urban; reference = rural). x_{tij} is the vector of control variables. β_0 is the intercept. β_1 is the WFI. β_2 is the BFI. β_3, β_4, and β_5 for the vectors of coefficients for urbanicity categories, within-effects of controls, and between-effects of controls, respectively. $\beta_6 Year_{ij}$ is the vector of year-fixed effects. V_{0j} is the state-level random intercept. V_{1j} is the state-level random slope of the WFI. V_{2j} is the state-level random slope of the BFI. U_{0ij} is the county-level random intercept. U_{1ij} is the county-level random slope of the WFI. R_{tij} is the observation-level error.

REWB models allow for estimating both within-effects and between-effects (Bell et al., 2019; Schunck, 2013). This is a notable strength in examining both dynamic changes within communities and wider social contexts between communities. REWB models have all the strengths of both fixed effects and random effects models. The within-effects are equivalent to the fixed-effect estimates of fixed effects models. Further, like random effects models, REWB models allow for estimating the effects of time-invariant variables. REWB models can also include random slopes that allow within-effects of community conditions to vary between communities, which often occurs in empirical data. A simulation study found that including random slopes can generate conservative standard errors and increase robustness from the normality assumption violation of random intercepts (Bell et al., 2019).

We estimated REWB models for each of 12 dependent variables (see Table 1). For reliable race/ethnicity-specific CMR rates, county-year observations with less than 300 race/ethnicity-specific children were excluded from analysis (521 county-year observations for Black CMR rates and 85 county-year observations for Latino CMR rates). For total and White CMR rates, all counties had more than 300 total children and also 300 White children. A few outliers (outside ± 4.5 interquartile range) were excluded during analysis (e.g., 3 county-year observations for total CMR rates). For Black- and Latino-specific analyses, county-year observations with missing controls (i.e., median income) were further excluded (82 county-year observations for Black CMR rates and 38 county-year observations for Latino CMR rates).

We used R for analysis, specifically the *lme4* package to estimate REWB linear models. Confidence intervals (CIs) were estimated by a bootstrap method. Some dependent variables with low occurrence rates (i.e., Black, Latino, physical abuse, and sexual abuse report rates) were positively skewed (skewness = 1.2 to 1.4). Yet, sensitivity analysis using REWB negative binomial models showed consistent findings. We report results of the REWB linear models.

Results

Table 1 reports the descriptive statistics. On average, 56.8 per 1,000 county children had a CMR annually. CMR rates were higher for younger children and for Black children than other racial/ethnic groups. There was little difference in CMR rates by child gender. Neglect was the most frequent type of child maltreatment, followed by physical abuse and sexual abuse. Among county residents, 14.4% were in a food-insecure household in a year on average.

Table 2 presents results of REWB models for total CMR rates. The BFI was statistically significant ($p < .05$) in all models, indicating that in inter-county comparisons, counties with higher food insecurity rates had significantly higher CMR rates. Specifically, every 1 per 100 increase in food insecurity rate was significantly associated with a 4.88 per 1,000 increase in CMR rate with no control (Model 1) and about 3 per 1,000 increase in CMR rate with controls (Model 2-4). Neither adding the “BFI × urbanicity” interaction nor adding a state-level random slope of BFI improved model fit (results not shown), suggesting consistency of the BFI-CMR relationship by urbanicity and state.

Regarding WFI, we report Model 4 results here since it shows the highest model fit among Models 1 to 4 (Table 2). Model 4 revealed that when counties’ food insecurity rates increased longitudinally, their CMR rates significantly increased over time in large urban counties, but not in small urban and rural counties. For rural counties, the WFI main term was not significant (coefficient = 0.01), suggesting the WFI-CMR relationship was not significant in rural counties (= the reference group). Specifically, when rural counties’ food insecurity rates increased by 1 per 100 over time, their CMR rates increased by 0.01 per 1,000 over time (95% CI = −1.46, 1.61) and failed to meet the criterion for statistical significance. Regarding large urban counties, the “WFI × large urban” interaction term was significant (coefficient = 1.59; 95% CI = 0.68, 2.39), suggesting the WFI-CMR relationship was significantly stronger in large urban counties than in rural counties. The WFI-CMR relationship specific to large urban counties can be computed by the sum of the WFI main term’s coefficient (= 0.01) and the “WFI × large urban” interaction term’s coefficient (= 1.59). That is, when large urban counties’ food insecurity rates increased by 1 per 100 annually, their CMR rates significantly increased by 1.60 annually (= 0.01 + 1.59; 95% CI = 0.09, 3.12; here we computed the CI based on the variance sum law). With regard to small urban counties, the “WFI × small urban” interaction term was not significant (coefficient = 0.70, 95% CI = −0.10, 1.50), suggesting the WFI-CMR relationship did not significantly differ between small urban and rural counties. For each year increase in food insecurity rate, CMR rates nonsignificantly increased by 0.71 (= 0.01 + 0.70; 95% CI = −0.77, 2.19) in small urban counties.

Next, we assessed whether food insecurity rates were associated with CMR rates, independent of child poverty rates. Further controlling for child poverty rates introduced moderate multicollinearity concerns (VIF = 5.29 to 5.85) but made little change in the BFI-CMR and WFI-CMR relationships in terms of direction (i.e., positive) and statistical significance of relationships (Models 4 and 5 in Table 2). This indicated that independent of child poverty rates and other confounders, the BFI-CMR relationship among all counties and the WFI-CMR relationship among large urban counties were significant.

Table 3 shows results within each subgroup of child age, child gender, child race/ethnicity, and maltreatment type. To avoid multicollinearity, the subgroup models did not control for child poverty while all other control variables were adjusted for. We reported coefficients relative to the mean of the dependent variable (= $M(Y)$), as well as raw coefficients, to make coefficients more comparable between subgroups with widely different outcome rates (e.g., neglect versus sexual abuse).

The BFI-CMR association was significant for all age groups (Table 3). That is, in inter-county comparisons, counties with higher food insecurity rates had higher CMR rates among all young (age 0-5), middle (age 6-11), and older (age 12-17) children. In terms of coefficients relative to $M(Y)$, when counties had 1 per 100 higher food insecurity rates, their CMR rates were about 5% higher for all age groups. The “WFI × urbanicity” interaction was significant in all age groups consistently and in accordance with the results for overall CMR rates. That is, the WFI-CMR relationship was highest and significant in large urban counties, somewhat higher but mostly nonsignificant in small urban counties, and lowest and nonsignificant in rural counties. There was no significant difference in BFI-CMR and WFI-CMR relationships by age group.

The gender-specific results (Table 3) were also consistent with the overall results. We found no significant difference in BFI-CMR and WFI-CMR relationships by gender group.

For child race/ethnicity, the results for White children were consistent with the overall results. Yet, the results for Black and Latino children were inconsistent with the overall results. Specifically, the BFI-CMR relationship was not significant for Black children, and the WFI-CMR relationship in large urban counties was not significant for Latino children. These findings might be due to this study’s use of overall food insecurity rates and the lack of data on race/ethnicity-specific food insecurity rates (see the Discussion section for details).

With regard to maltreatment type, the BFI-CMR relationship was significant for not only neglect report rates, but also physical abuse and sexual abuse report rates. The WFI × urbanicity interaction on neglect report rates was significant and consistent with the overall results. However, this interaction was not significant for physical abuse or sexual abuse report rates.

Discussion

To our knowledge, this study is the first to report the county-level associations between food insecurity rates and CMR rates, using U.S. national county-level data from 2009-2018. While controlling for a range of confounders, we found that higher food insecurity rates were associated with increased CMR rates in inter-county comparisons (i.e., between-effects) among all urban and rural counties, as well as in within-county longitudinal changes (i.e., within-effects) among large urban counties. That is, for between-effects, when comparing multiple counties cross-sectionally we found that counties with higher food insecurity rates had higher CMR rates consistently among all large urban, small urban, and rural counties. This between-effect finding helps understand the relationship in a broad spectrum of social contexts. For example, according to our estimated model, when the food insecurity rate increased from 12% (25^{th} percentile of U.S. counties) to 17% (75^{th} percentile of U.S. counties), the CMR rate is expected to increase from 46 per 1,000 children to 59 per 1,000 children while all other controlled conditions were fixed to their means. For within-effects, we found that increasing food insecurity rates over time only predicted rising CMR rates for large urban counties. However, over 50% of U.S. children resided in large urban counties in this study's data. This within-effect finding illuminates the relationship in longitudinal dynamics. The within-effects also enhance confidence in causality by eliminating unobserved time-invariant heterogeneity, although unobserved time-varying conditions can still confound the relationship. All these findings about the between-effects and the within-effects were consistent overall and within most subgroups of age, gender, and maltreatment type.

The present findings extend the previous findings in two important ways. First, we examine community-level relationships. Virtually all previous studies examined how family-level food insecurity status was related to a child's risk of being abused or neglected (Epstein, 2001; Garg et al., 2019; Helton et al., 2019; Mersky & Janczewski, 2018; Slack et al., 2011; Yang, 2015). An individual-level relationship can but does not always drive a community-level relationship. Indeed researchers dubbed the logical fallacy of inferring group-level associations from individual-level data the "atomistic fallacy" (Diez-Roux, 1998). The current study addresses this knowledge gap by revealing that community-level findings are consistent with prior individual-level findings, both showing positive relationships between food insecurity and child maltreatment. Theoretically, while the current study examines no specific causal pathways, it provides a foundation for future research on community-level causal mechanisms. Practically, along with the growing emphasis on ecological models of social and public health problems, community-based approaches have gained popularity and become a vital intervention approach in social work and public health (Graaf & Ratliff, 2018; Merzel & D'Afflitti, 2003). The current study offers evidence supporting community-based interventions in high food insecure communities to address high rates of both food insecurity and child maltreatment reporting. Second, the current study helps generalize previous findings by using national data on general populations. Previous findings are based on local, mostly urban populations with lower incomes or at higher risk for child maltreatment (Epstein, 2001; Garg et al., 2019; Helton et al., 2019; Mersky & Janczewski, 2018; Slack et al., 2011; Yang, 2015). Yet, public health approaches aiming population-level impacts on child maltreatment prevention require evidence that helps assess risks across the full population and develop large-scale policies (Covington, 2013). The present study provides empirical evidence supporting a positive community-level relationship between food insecurity and child maltreatment reporting in the U.S. general population. While further research is needed, this finding suggests potential benefits of large-scale policy efforts to lower food insecurity rates.

Some unexpected and interesting findings warrant further discussion. For example, the association between the WFI and CMR rates significantly differed by urbanicity. This association was largest and statistically significant among large urban counties, smaller and hardly significant among small urban counties, and smallest and nonsignificant among rural counties, overall and within subgroups. Although we cannot offer a clear explanation for this interaction, some speculations are possible. First, the difference in longitudinal trends of CMR rates by urbanicity, especially larger increases in small urban and rural counties, might mask the WFI. During the study period (2009-2018), national CMR rates increased most rapidly in rural counties, less rapidly in small urban counties, and least rapidly in large urban counties (Kim & Maguire-Jack, 2021). A prior study found that this upward trend was observed mostly among CMRs from professional reporters (e.g., teachers and doctors), but almost not among CMRs from non-professional reporters (e.g., friends and neighbors; Kim & Maguire-Jack, 2021). This suggested that factors other than increases in child maltreatment *incidents* (e.g., increasing awareness among professional reporters) might drive increases in CMRs. If this was the case, the larger increases in CMRs in rural and small urban counties might mask the longitudinal association between food insecurity and child maltreatment. On the other hand, perhaps as-yet-unknown protective factors in rural and small urban counties prevented the WFI from leading to CMR rates. Emerging evidence suggests that the contexts of child maltreatment considerably differ by urbanicity. More research is required to understand potential protective and risk functions of urban-rural contexts and their interactions with food insecurity contexts. Other explanations might also be possible.

For race/ethnicity, the BFI was most notable among White children, but considerably smaller among Latino children and not significant among Black children. This was perhaps due to our use of overall food insecurity, which might represent food insecurity contexts of White residents, the majority population in most counties. The contextual-level difference in food insecurity by race/ethnicity can be huge, as suggested by poverty disparities. The risk of living in high poverty neighborhoods is about 10 times higher for Black and Latino children than for White children, whereas the individual-level poverty risk is about two times higher for Black and Latino children than for White children (Drake & Rank, 2009). More research considering race/ethnicity-specific contexts of food insecurity is needed.

Strengths/Limitations

A strength of this study is the use of national data including both urban and rural populations. Using county-level data of food insecurity estimated by the MMG study and the national CMR data made this possible. The subgroup-specific analysis is also a strength to understand the relationship specific to important urban-rural, demographic, and maltreatment type subgroups. Another strength is the application of REWB models, allowing for examination of both within-effects and between-effects.

This study has several limitations, which warrant caution when interpreting its findings. First, while this study’s findings have strong generalizability for community-level relationships, implications for individual-level relationships are limited. Second, the present findings are based on observational data rather than experimental data, and therefore have limited implications for causality. Third, compared with the BFI, the WFI has greater implications for causality by accounting for time-invariant unobserved heterogeneity. However, longitudinal changes of CMR rates can be vulnerable to changes of surveillance and reporting behaviors, and thus not reflect changes in actual child maltreatment incidents (Kim & Maguire-Jack, 2021). More research is required to understand the drivers of the longitudinal changes of CMR rates and the identified interaction between the with-effect of food insecurity and urbanicity. Fourth, although national data were available at only the county level, counties may be too large to ensure similar contextual experiences among residents. Race/ethnicity-specific measures might address this concern to some degree (e.g., Kim & Drake, 2018), but such measures of community food insecurity are currently unavailable. Expanding the MMG measurement method to smaller areas (e.g., zip codes and census tracts) may help address this limitation in future research. Finally, this study's findings are about reported child maltreatment cases. Many child maltreatment incidents are never reported to CPS agencies (Sedlak et al., 2010), and certain maltreatment types may be more likely to be so. For example, although emotional abuse is often found the most prevalent type in survey data (Finkelhor et al., 2015), it is one of the least prevalent types among reported child maltreatment cases (U.S. Department of Health and Human Services, 2021). Implications for unreported child maltreatment incidents and under-reported maltreatment types (e.g., emotional abuse) should be drawn cautiously.

Implications

Although no clear causality has yet been established, the strong correlational evidence, including the evidence reported here, warrants addressing food insecurity as a means to prevent child maltreatment occurring and reporting. Randomization for many risk factors (e.g., poverty, food insecurity, and depression) is impossible practically and ethically. Policies and programs can be developed with correlational factors, and evaluations of their effectiveness may help establish causality in a post-hoc manner. As Conrad-Hiebner and Scanlon (2015) suggest, at the minimum, addressing food insecurity appears unlikely to do any harm and likely to reduce socioeconomic disparities.

Food insecurity screening as a routine practice for professionals working with children and their families may help early identification and intervention. Household food insecurity can be assessed by the 18-item CFSM. For brief surveys, shorter versions are available, such as a 6-item version (Blumberg et al., 1999) and a 2-item version (Hager et al., 2010). Our findings further suggest that routine assessments of community food insecurity may help identify high-risk communities and allocate resources accordingly. While no direct measure is available for all U.S. communities, the MMG provides *estimated* food insecurity rates for all U.S. counties annually from 2009 and on (Feeding America, n.d.). Ideally, for periodic direct measurement, the Census Bureau may be able to consider adding a food insecurity questionnaire to future ACS.

The strong community-level association between food insecurity rates and CMR rates suggests that coordinated and collaborative approaches are required to address these co-existing issues in communities. Interdisciplinary efforts between nutrition, child welfare, public health, medical, education, and other professionals may help promote health and well-being of families and their children exposed to these adversities. Enhancing accessibility to existing government and community programs known to reduce food insecurity (e.g., the Supplemental Nutrition Assistance Program, the National School Lunch/Breakfast Program, and the Special Supplemental Nutrition Program for Women, Infants, and Children) as a part of interdisciplinary efforts would be an easy and effective way to help children and families, given the underutilization of these programs by eligible families (Gundersen & Ziliak, 2018). For a practical application, interdisciplinary efforts and service utilization can be enhanced by co-locating food insecurity services (e.g., food insecurity screening, emergency food boxes, and referral services) within other service settings, such as schools, hospitals, social service agencies, child welfare agencies, and other community settings (Gottlieb et al., 2013).

While existing prevention programs largely focus on psychological approaches, a number of evidence-based programs including home-based models (e.g., Child First, Healthy Beginnings, and Minding the Baby Home Visiting) and center-based models (e.g., Safe Environment for Every Kid) have service components for food hardships (CEBC, n.d.; HomeVEE, n.d.). These components include food insecurity screening, facilitating access to eligible food assistance programs, coordination and collaboration to alleviate food hardships, and education and training for staff and clients on topics related to nutrition and food insecurity. To the extent that a causal relationship exists between food insecurity and child maltreatment, adding these service components to community services may help reduce food insecurity rates and eventually child maltreatment rates in communities.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Funding/Acknowledgement:

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

Baum WM, & Kupfer AS (2005). Behavior analysis, evolutionary theory, and the corporal discipline of children. In Donnelly M & Straus MA (Eds.), Corporal punishment of children in theoretical perspective (pp. 103–133). Yale University Press.

Bell A, Fairbrother M, & Jones K (2019). Fixed and random effects models: Making an informed choice. Quality & Quantity, 53(2), 1051–1074. 10.1007/s11135-018-0802-x

Belsky J (1993). Etiology of child maltreatment: A developmental-ecological analysis. Psychological Bulletin, 114(3), 413–434. 10.1037/0033-2909.114.3.413 [PubMed: 8272464]

Bickel G, Nord M, Price C, Hamilton W, & Cook J (2000). Guide To Measuring Household Food Security, revised 2000. U.S. Department of Agriculture, Food and Nutrition Service.

Blumberg SJ, Bialostosky K, Hamilton WL, & Briefel RR (1999). The effectiveness of a short form of the Household Food Security Scale. American Journal of Public Health, 89(8), 1231–1234. 10.2105/AJPH.89.8.1231 [PubMed: 10432912]

CEBC. (n.d.). Safe Environment for Every Kid. https://www.cebc4cw.org/program/safe-environment-for-every-kid-seek-model/

Child Welfare Information Gateway. (2019). Definitions of child abuse and neglect. https://www.childwelfare.gov/pubpdfs/define.pdf

Coleman-Jensen A, Rabbitt MP, Gregory CA, & Singh A (2020). Household food security in the United States in 2019. U.S. Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/publications/pub-details/?pubid=99281

Conger RD, Conger KJ, Elder GH, Lorenz FO, Simons RL, & Whitbeck LB (1992). A family process model of economic hardship and adjustment of early adolescent boys. Child Development, 63(3), 526–541. 10.1111/j.1467-8624.1992.tb01644.x [PubMed: 1600820]

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

Conrad-Hiebner A, & Scanlon E (2015). The economic conditions of child physical abuse: A call for a national research, policy, and practice agenda. Families in Society: The Journal of Contemporary Social Services, 96(1), 59–66. 10.1606/1044-3894.2015.96.8

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]

Covington T (2013). The public health approach for understanding and preventing child maltreatment: A brief review of the literature and a call to action. Child Welfare, 92(2), 21–39. http://search.proquest.com/docview/1464748069?accountid=15159 [PubMed: 24199321]

Diez-Roux AV (1998). Bringing context back into epidemiology: variables and fallacies in multilevel analysis. American Journal of Public Health, 88(2), 216–222. 10.2105/AJPH.88.2.216 [PubMed: 9491010]

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

Drake B, & Jonson-Reid M (2014). Poverty and child maltreatment. In Korbin JE & Krugman RD (Eds.), Handbook of child maltreatment (pp. 131–148). Springer Netherlands.

Drake B, & Rank MR (2009). The racial divide among American children in poverty: Reassessing the importance of neighborhood. Children and Youth Services Review, 31(12), 1264–1271. 10.1016/j.childyouth.2009.05.012

Epstein MR (2001). Predicting abuse and neglect in the first two years of life from risk assessment during the prenatal and perinatal period [University of California, Davis]. https://www.proquest.com/docview/251483734

Feeding America. (n.d.). Food insecurity in the United States. https://map.feedingamerica.org/

Feeding America. (2021). Map the Meal Gap 2021: Technical appendix. Feeding America. https://www.feedingamerica.org/research/map-the-meal-gap/how-we-got-the-map-data

Fiese BH, Gundersen C, Koester B, & Jones B (2016). Family chaos and lack of mealtime planning is associated with food insecurity in low income households. Economics & Human Biology, 21, 147–155. 10.1016/j.ehb.2016.01.004 [PubMed: 26907770]

Finkelhor D, Turner HA, Shattuck A, & Hamby SL (2015). Prevalence of childhood exposure to violence, crime, and abuse. JAMA Pediatrics, 169(8), 746–754. 10.1001/jamapediatrics.2015.0676 [PubMed: 26121291]

Garg A, Tripodis Y, Dworsky ZD, & Sege RD (2019). Do basic unmet maternal needs influence infant maltreatment risk? A nested case-control study. Clinical Pediatrics, 58(4), 461–465. 10.1177/0009922818821879 [PubMed: 30623689]

Gottlieb L, Sandel M, & Adler NE (2013). Collecting and Applying Data on Social Determinants of Health in Health Care Settings. JAMA Internal Medicine, 173(11), 1017. 10.1001/jamainternmed.2013.560 [PubMed: 23699778]

Graaf G, & Ratliff GA (2018). Preparing social workers for evidence-informed community-based practice: An integrative framework. Journal of Social Work Education, 54(sup1), S5–S19. 10.1080/10437797.2018.1434437

Gundersen C, Engelhard E, & Waxman E (2014). Map the Meal Gap: Exploring food insecurity at the local level. Applied Economic Perspectives and Policy, 36(3), 373–386. 10.1093/aepp/ppu018

Gundersen C, & Ziliak JP (2015). Food insecurity and health outcomes. Health Affairs, 34(11), 1830–1839. 10.1377/hlthaff.2015.0645 [PubMed: 26526240]

Gundersen C, & Ziliak JP (2018). Food Insecurity Research in the United States: Where We Have Been and Where We Need to Go. Applied Economic Perspectives and Policy, 40(1), 119–135. 10.1093/aepp/ppx058

Hager ER, Quigg AM, Black MM, Coleman SM, Heeren T, Rose-Jacobs R, Cook JT, de Cuba SAE, Casey PH, Chilton M, Cutts DB, Meyers AF, & Frank DA (2010). Development and validity of a 2-item screen to identify families at risk for food insecurity. Pediatrics, 126(1), e26–e32. 10.1542/peds.2009-3146 [PubMed: 20595453]

Heflin CM, Siefert K, & Williams DR (2005). Food insufficiency and women's mental health: Findings from a 3-year panel of welfare recipients. Social Science & Medicine, 61(9), 1971–1982. 10.1016/j.socscimed.2005.04.014 [PubMed: 15927331]

Helton JJ, Jackson DB, Boutwell BB, & Vaughn MG (2019). Household food insecurity and parent-to-child aggression. Child Maltreatment, 24(2), 213–221. 10.1177/1077559518819141 [PubMed: 31094579]

HomeVEE. (n.d.). Model implementation summary reports. https://homvee.acf.hhs.gov/implementation

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]

Jackson DB, Lynch KR, Helton JJ, & Vaughn MG (2018). Food insecurity and violence in the home: Investigating exposure to violence and victimization among preschool-aged children. Health Education & Behavior, 45(5), 756–763. 10.1177/1090198118760683 [PubMed: 29532691]

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, & Maguire-Jack K (2021). Longitudinal changes in child maltreatment reports. American Journal of Orthopsychiatry. 10.1037/ort0000565

Knowles M, Rabinowich J, Ettinger de Cuba S, Cutts DB, & Chilton M (2016). "Do you wanna breathe or eat?": Parent perspectives on child health consequences of food insecurity, trade-offs, and toxic stress. Maternal and Child Health Journal, 20(1), 25–32. 10.1007/s10995-015-1797-8 [PubMed: 26156827]

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]

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

Marques ES, Reichenheim ME, de Moraes CL, Antunes MM, & Salles-Costa R (2015). Household food insecurity: a systematic review of the measuring instruments used in epidemiological studies. Public Health Nutrition, 18(5), 877–892. 10.1017/S1368980014001050 [PubMed: 24963759]

Mersky JP, & Janczewski CE (2018). Racial and ethnic differences in the prevalence of adverse childhood experiences: Findings from a low-income sample of U.S. women. Child Abuse & Neglect, 76, 480–487. 10.1016/j.chiabu.2017.12.012 [PubMed: 29272816]

Merzel C, & D'Afflitti J (2003). Reconsidering community-based health promotion: Promise, performance, and potential. American Journal of Public Health, 93(4), 557–574. 10.2105/AJPH.93.4.557 [PubMed: 12660197]

National Research Council. (2006). Food insecurity and hunger in the United States. National Academies Press. 10.17226/11578

Oliveira KHD, Almeida GM, Gubert MB, Moura AS, Spaniol AM, Hernandez DC, Pérez-Escamilla R, & Buccini G (2020). Household food insecurity and early childhood development: Systematic review and meta-analysis. Maternal & Child Nutrition, 16(3). 10.1111/mcn.12967

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]

Sampson RJ, Morenoff JD, & Earls F (1999). Beyond social capital: Spatial dynamics of collective efficacy for children. American Sociological Review, 64(5), 633. 10.2307/2657367

Schunck R (2013). Within and between estimates in random-effects models: Advantages and drawbacks of correlated random effects and hybrid models. The Stata Journal: Promoting Communications on Statistics and Stata, 13(1), 65–76. 10.1177/1536867X1301300105

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.

Shankar P, Chung R, & Frank DA (2017). Association of food insecurity with children's behavioral, emotional, and academic outcomes: A systematic review. Journal of Developmental & Behavioral Pediatrics, 38(2), 135–150. 10.1097/DBP.0000000000000383 [PubMed: 28134627]

Slack KS, Berger LM, DuMont K, Yang M-Y, Kim B, Ehrhard-Dietzel S, & Holl JL (2011). Risk and protective factors for child neglect during early childhood: A cross-study comparison. Children and Youth Services Review, 33(8), 1354–1363. 10.1016/j.childyouth.2011.04.024

Stith SM, Liu T, Davies LC, Boykin EL, Alder MC, Harris JM, Som A, McPherson M, & Dees JEMEG (2009). Risk factors in child maltreatment: A meta-analytic review of the literature. Aggression and Violent Behavior, 14(1), 13–29. https://doi.org/10.1016/j.avb.2006.03.006

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

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]

Table 1.

Descriptive Statistics

Variable	Mean (SD) or %
Dependent Variables – Child Maltreatment Report Rate	
Total	
Total: # reported children per 1k children (N_1=6150; N_2=639; N_3=51)	56.8 (27.2)
By Child Age	
Young: # reported children per 1k children aged 0-5 years (N_1=6150; N_2=639; N_3=51)	71.2 (35.6)
Middle: # reported children per 1k children aged 6-11 years (N_1=6150; N_2=639; N_3=51)	58.5 (28.3)
Older: # reported children per 1k children aged 12-17 years (N_1=6150; N_2=639; N_3=51)	42.7 (20.7)
By Child Gender	
Male: # reported children per 1k male children (N_1=6150; N_2=639; N_3=51)	55.5 (26.6)
Female: # reported children per 1k female children (N_1=6150; N_2=639; N_3=51)	57.5 (27.4)
By Child Race/Ethnicity	
White: # reported children per 1k White children (N_1=6152; N_2=639; N_3=51)	47.7 (26.9)
Black: # reported children per 1k Black children (N_1=5534; N_2=606; N_3=51)	91.5 (50.4)
Latino: # reported children per 1k Hispanic/Latino children (N_1=6001; N_2=634; N_3=51)	43.8 (24.3)
By Maltreatment Type	
Neglect: # reported children for neglect per 1k children (N_1=6151; N_2=639; N_3=51)	39.4 (23.4)
Physical abuse (PA): # reported children for PA per 1k children (N_1=6120; N_2=639; N_3=51)	12.4 (7.6)
Sexual abuse (SA): # reported children for SA per 1k children (N_1=6147; N_2=639; N_3=51)	4.3 (2.9)
Independent Variables (based on data for total report rates)	
% persons in a food-insecure household	14.4 (3.2)
Control Variables (based on data for total report rates)	
Median owner-occupied house value per 10k	20.1 (11.7)
% foreign-born among persons	8.5 (7.5)
% children among persons	23.5 (3.0)
% male among adults aged 20-64 years	49.7 (1.5)
% moved in one year among persons	15.7 (4.0)
% children in poverty	20.8 (7.5)
Urbanicity	
Large urban: county in metro area with 1 million population or more	32.4%
Small urban: county in metro area with fewer than 1 million population	49.5%
Rural: nonmetro county	18.1%
Year	
2009	9.1%
2010	9.4%
2011	9.4%
2012	10.2%
2013	10.2%
2014	10.2%

Variable	Mean (SD) or %
2015	10.4%
2016	10.4%
2017	10.4%
2018	10.4%

Note. N_1 = number of county-year observations. N_2 = number of counties. N_3 = number of states.

Table 2.

Random Effects Within-Between Models of Child Maltreatment Report Rates, U.S. Counties, 2009-2018.

	Child Maltreatment Report Rate per 1,000 Children				
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Fixed Effects: Coef (95% CI)					
WFI	−0.09 (−0.58, 0.35)	0.04 (−0.36, 0.49)	**−0.75 (−1.26, −0.18)**	0.01 (−1.46, 1.61)	−0.58 (−2.18, 1.02)
BFI	**4.88 (4.40, 5.38)**	**3.16 (2.63, 3.74)**	**3.16 (2.62, 3.64)**	**3.05 (2.50, 3.57)**	**2.13 (0.96, 3.08)**
WFI×Large Urban	–	–	**1.67 (1.11, 2.25)**	**1.59 (0.68, 2.39)**	**1.57 (0.76, 2.40)**
WFI×Small Urban	–	–	**0.76 (0.19, 1.27)**	0.70 (−0.10, 1.50)	0.62 (−0.17, 1.41)
Random Slopes: Variance					
County-Level WFI	–	–	–	6.92	6.82
State-Level WFI	–	–	–	21.32	21.64
Other Terms in the Model	Random intercepts; Year fixed effects	Random intercepts; Year fixed effects; Controls	Random intercepts; Year fixed effects; Controls	Random intercepts; Year fixed effects; Controls; Interaction terms	Random intercepts; Year fixed effects; Controls; Interaction terms; Within-effect and between-effect of child poverty
Model Fit: AIC	46296.6	46069.1	46031.2	44359.2	44329.2

Note. Coef = coefficient. CI = confidence interval. WFI = within-effect of food insecurity rates. BFI = between-effect of food insecurity rates. Sample size = 6,150 county-year observations nested in 639 counties and 51 states (50 states and DC). Significant coefficients ($p < .05$) are in boldface. Controls include urbanicity and within-effects and between-effects of median owner-occupied house value, % foreign born among persons, % children among persons, % male among adults aged 20-64 years, and % moved in one year among persons. A lower value of Akaike Information Criterion indicates a better model fit.

Table 3.

Random Effects Within-Between Models by Child Age, Gender, Race/Ethnicity, and Maltreatment Type, U.S. Counties, 2009-2018.

	Child Maltreatment Report Rate per 1,000 Children in Each Group					
	Coefficient (95% CI)			Coefficient Relative to Mean Y (95% CI)		
By Child Age	**Age 0-5** *(N_1=6150; N_2=639; N_3=51)*	**Age 6-11** *(N_1=6150; N_2=639; N_3=51)*	**Age 12-17** *(N_1=6150; N_2=639; N_3=51)*	**Age 0-5** *(Mean Y = 71.2)*	**Age 6-11** *(Mean Y = 58.5)*	**Age 12-17** *(Mean Y = 42.7)*
WFI	−0.12 (−1.94, 1.59)	0.53 (−1.07, 2.35)	−0.42 (−1.64, 0.91)	−0.16% (−2.73, 2.23)	0.90% (−1.83, 4.02)	−0.99% (−3.85, 2.13)
BFI	**3.84 (3.12, 4.55)**	**3.08 (2.55, 3.67)**	**2.24 (1.87, 2.67)**	**5.40% (4.38, 6.40)**	**5.27% (4.35, 6.28)**	**5.25% (4.38, 6.25)**
WFI×Large Urban	**1.53 (0.40, 2.65)**	**1.13 (0.02, 2.11)**	**1.96 (1.21, 2.77)**	**2.16% (0.56, 3.73)**	**1.93% (0.04, 3.61)**	**4.59% (2.83, 6.50)**
WFI×Small Urban	0.81 (−0.14, 1.88)	0.16 (−0.74, 1.04)	**0.99 (0.26, 1.72)**	1.14% (−0.20, 2.64)	0.28% (−1.26, 1.78)	**2.33% (0.62, 4.04)**
By Child Gender	**Male** *(N_1=6150; N_2=639; N_3=51)*	**Female** *(N_1=6150; N_2=639; N_3=51)*		**Male** *(Mean Y = 55.5)*	**Female** *(Mean Y = 57.5)*	
WFI	−0.30 (−1.76, 1.24)	0.15 (−1.22, 1.61)		−0.55% (−3.16, 2.24)	0.26% (−2.13, 2.80)	
BFI	**2.94 (2.39, 3.45)**	**3.16 (2.63, 3.77)**		**5.30% (4.32, 6.22)**	**5.50% (4.57, 6.56)**	
WFI×Large Urban	**1.78 (0.85, 2.65)**	**1.40 (0.58, 2.26)**		**3.21% (1.53, 4.78)**	**2.43% (1.01, 3.92)**	
WFI×Small Urban	**0.86 (0.10, 1.70)**	0.55 (−0.14, 1.36)		**1.55% (0.18, 3.07)**	0.96% (−0.24, 2.36)	
By Child Race/Ethnicity	**White** *(N_1=6152; N_2=639; N_3=51)*	**Black** *(N_1=5534; N_2=606; N_3=51)*	**Latino** *(N_1=6001; N_2=634; N_3=51)*	**White** *(Mean Y = 47.7)*	**Black** *(Mean Y = 91.5)*	**Latino** *(Mean Y = 43.8)*
WFI	−0.18 (−1.58, 1.12)	1.34 (−2.62, 5.19)	−0.52 (−2.42, 1.36)	−0.39% (−3.32, 2.35)	1.46% (−2.87, 5.67)	−1.18% (−5.51, 3.11)
BFI	**3.41 (2.81, 4.04)**	0.92 (−0.35, 2.26)	**1.14 (0.49, 1.74)**	**7.15% (5.89, 8.46)**	1.01% (−0.38, 2.47)	**2.59% (1.12, 3.96)**
WFI×Large Urban	**1.99 (1.11, 2.68)**	**3.25 (0.32, 5.84)**	1.03 (−0.18, 2.32)	**4.17% (2.33, 5.62)**	**3.56% (0.35, 6.38)**	2.34% (−0.41, 5.28)
WFI×Small Urban	0.70 (−0.00, 1.47)	0.29 (−2.37, 2.92)	0.39 (−0.79, 1.64)	1.47% (−0.00, 3.08)	0.32% (−2.59, 3.20)	0.88% (−1.80, 3.74)
By Maltreatment Type	**Neglect** *(N_1=6151; N_2=639; N_3=51)*	**Physical Abuse** *(N_1=6120; N_2=639; N_3=51)*	**Sexual Abuse** *(N_1=6147; N_2=639; N_3=51)*	**Neglect** *(Mean Y = 39.4)*	**Physical Abuse** *(Mean Y = 12.4)*	**Sexual Abuse** *(Mean Y = 4.3)*
WFI	0.45 (−0.96, 1.75)	−0.39 (−1.09, 0.33)	0.01 (−2.42, 1.36)	1.13% (−2.44, 4.44)	−3.18% (−8.80, 2.64)	0.20% (−3.04, 3.26)
BFI	**2.03 (1.61, 2.49)**	**0.53 (0.39, 0.69)**	**0.24 (0.49, 1.74)**	**5.16% (4.08, 6.33)**	**4.30% (3.14, 5.58)**	**5.64% (4.31, 6.85)**
WFI×Large Urban	**1.41 (0.65, 2.17)**	0.13 (−0.16, 0.43)	0.02 (−0.18, 2.32)	**3.59% (1.66, 5.50)**	1.04% (−1.31, 3.48)	0.54% (−1.72, 2.66)
WFI×Small Urban	**0.82 (0.13, 1.50)**	−0.06 (−0.31, 0.21)	0.03 (−0.79, 1.64)	**2.08% (0.32, 3.80)**	−0.52% (−2.50, 1.73)	0.76% (−1.14, 2.77)

Note. CI = confidence interval. N_1 = number of county-year observations. N_2 = number of counties. N_3 = number of states. WFI = within-effect of food insecurity rates. BFI = between-effect of food insecurity rates. Significant coefficients ($p < .05$) are in boldface. Each model controlled for year fixed effects, urbanicity, and within-effects and between effects of median owner-occupied house value, % foreign born among persons, % children among persons, % male among adults aged 20-64 years, % moved in one year among persons. For race/ethnicity-specific models, race/ethnicity-specific variables (e.g., % foreign-born among White persons) were used for the following variables: % foreign born, % children, % male, and % moved.