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Evidence-Based Home Visiting Provisions and Child Maltreatment Report Rates: County-Level Analysis of U.S. National Data from 2016 to 2018

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Abstract

This observational ecological study examined county-level associations between evidence-based home visiting (EHV) provisions and child maltreatment report (CMR) rates, using national county-level data from 2016-2018. We found that longitudinal changes of EHV provisions were significantly negatively associated with county CMR rates while controlling for potential confounders. Our model estimated that after EHV provisions were launched in counties, their CMR rates decreased (or after they were ceased, rates increased) by 2.21 per 1,000 children overall, 2.88 per 1,000 children aged 0-5, 2.59 per 1,000 children aged 6-11, 2.13 per 1,000 male children, and 2.24 per 1,000 female children. When limiting attention to EHV provisions funded by the Maternal, Infant and Early Childhood Home Visiting (MIECHV) program, we found no significant association perhaps because MIECHV-funded EHV provisions were a small subset of all EHV provisions. These findings propose potential protective impacts of county EHV provisions on overall county CMR rates. Yet, the small effect sizes suggest that EHV provisions should be considered as a part of a complete response to child maltreatment rather than in isolation. Given that EHV is provided to a very small part of the population, nevertheless, our findings suggest that expanding coverage would increase effect sizes.

Introduction

Child maltreatment is a major national concern. Over 1 in 22 U.S. children are reported to and investigated by child protective services (CPS) for child maltreatment concerns each year (DHHS, 2021). An estimated 1 in 3 U.S. children will be investigated by CPS by age 18 (Kim et al., 2017). Child maltreatment has been linked to myriad biological, psychological, and social problems, including premature death (Anda et al., 2006; Cabrera et al., 2020; Lansford et al., 2002; Vaithianathan et al., 2018). A recent estimate suggests that the societal lifetime cost of all investigated child maltreatment reports (CMRs) in a single year in the United States is $2 trillion (Peterson et al., 2018). Understanding community risk and protective factors is important to inform prevention efforts (Jones Harden et al., 2020). Prior research has heavily focused on community risk factors (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014a). Yet, research on community protective

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factors is sparse. Research on community-level provisions of evidence-based home visiting (EHV) in particular has been absent, even though EHV has been the most prominent approach for child maltreatment prevention. Most studies of the impacts of EHV have been individual-level randomized controlled trials. From a public health and program evaluation standpoint, however, examining impacts on a whole community offers the opportunity to better assess the value of these programs with regard to their effectiveness in real-world community settings and the possibility of spillover effects through a variety of mechanisms. To address this knowledge gap, this study examines the county-level relationship between EHV provisions and CMR rates, using U.S. national data from 2016-2018.

Background

Early childhood EHV (hereafter just EHV) services in the United States are primarily voluntary services that aim to enhance a wide range of social, health, and educational outcomes of children and families (Fernandes-Alcantara, 2018; Finello et al., 2016). They are supported by strong evidence that prenatal and early childhood development has significant, long-lasting effects over the life course (Cannon et al., 2018). Practitioners, policy-makers, and researchers have considered EHV to be a premier strategy to prevent child maltreatment (Finello et al., 2016; Jones Harden et al., 2020). Most EHV programs involve professionals or paraprofessionals conducting weekly to monthly home visits for several years between the prenatal period and age 5 years (Fernandes-Alcantara, 2018; Finello et al., 2016). Common services include education/training, assessment/screening, coordination/referral, and intervention/support services that aim to promote parenting knowledge and skills, to improve developmental, physical, psychological, and behavioral conditions, and to enhance social, economic, and environmental conditions (Fernandes-Alcantara, 2018; Finello et al., 2016). Most EHV programs target high-risk populations rather than offering universal provisions (Fernandes-Alcantara, 2018; Finello et al., 2016). A recent meta-analytic review found that the overall effect of EHV programs on child maltreatment prevention was significant, but small (Gubbels et al., 2021). Experts generally recommend implementing EHV as part of an array of prevention efforts, recognizing that EHV has real, but small impact (Fernandes-Alcantara, 2018).

There are 21 home visiting models that satisfy the Department of Health and Human Services (DHHS) criteria for an EHV model, of which 16 models are operating in the United States (Fernandes-Alcantara, 2018; NHVRC, 2019). An ongoing systematic review funded by DHHS has found that four of these models have favorable findings for child maltreatment prevention, while the other 12 have favorable findings on other outcomes (e.g., positive parenting practices), which can be protective against child maltreatment (HomVEE, n.d.). This study limits its focus to these 16 EHV models (see Table S1 in the Supplement). The following four models have served the largest number of families among these models: Parents as Teachers, Healthy Families America, Early Head Start Home-Based Option, and Nurse-Family Partnership.

Theoretical Framework

There are several theoretical reasons to believe that EHV provision is likely to have a protective impact on community CMR rates. First, community EHV provision can simply lower CMR risk among service participants. This may decrease overall community CMR rates. Second, community EHV provisions can promote positive social processes. Communities with a concentration of high-risk families may be socially impoverished because many residents have low social resources to share, while their level of need is high. This may create a harmful imbalance between needs and resources and in turn increase CMR risk (Garbarino & Sherman, 1980). EHV programs generally focus on high-risk families and may help address challenges these families face and reduce the number of high-risk families in a community. This in turn may help alleviate social impoverishment to some degree, which can be protective against CMRs for resident families. Addressing social impoverishment may also help strengthen social support and cohesion, and in turn may enhance collective efficacy and engagement to prevent child maltreatment incidents and reports (Sampson et al., 1999). Finally, the existence of community services itself may be preventive against child maltreatment. Negative appraisals about community environments can be a source of stress. Social cognitive and stress-coping theories suggest that just perceiving the existence of community services can lessen such appraisals and can address feelings of stress even among non-participants (Maguire-Jack & Negash, 2016). This lowering of stress may ultimately lower community CMR rates. While we do not test any of these theoretical explanations, together they justify this inquiry.

Prior Studies

Studies of EHV programs have demonstrated some individual-level effects in reducing child maltreatment risk among participant families (Avellar & Supplee, 2013; HomVEE, n.d.). For example, studies have found that compared with non-participant families, participant families have lower risks of substantiated CMR, neglect report, substantiated physical or sexual abuse report, self-reported neglect, self-reported physical abuse, self-reported sexual abuse, and self-reported psychological abuse (Avellar & Supplee, 2013; HomVEE, n.d.). These findings are based on a rigorous research design, such as a randomized controlled trial, and have important causal implications at an individual level. However, they have limited implications for understanding impacts of EHV programs for a community as a whole including both service participants and non-participants.

No studies have evaluated community-level EHV provisions to our knowledge. Yet several have examined community-level impacts of other or more general community service provisions on child maltreatment. An experimental study evaluated county-level impacts of Triple P (Positive Parenting Program). This program has a home visiting component, but also various other components, such as media and informational strategies, parenting seminars and consultations, skills training, and group sessions (Prinz et al., 2009). Based on random assignment of 18 counties in a southeastern state, the study found that the Triple P counties showed lower rates of substantiated CMRs, foster care entries, and child maltreatment injuries than the control counties. A different county-level study on Triple P in North Carolina used a quasi-experimental design and found the Triple P counties had lower rates of CMRs and foster care entries than comparison counties (Schilling et al., 2020). A multilevel study on families in Wisconsin counties assessed spending on child maltreatment prevention programs (e.g., wraparound, domestic violence, mental health, substance abuse, parenting education, referral, respite care, support group, youth service, and home visiting).

The study found that increased spending in counties was associated with a decreased CMR risk among their resident families (Maguire-Jack, 2014b). A study based in Franklin County, Ohio, examined availability and accessibility of neighborhood social services, such as medical, mental health, childcare, and basic needs (Maguire-Jack & Negash, 2016). It found that having more available neighborhood services was related to lower risks of neglect and physical abuse and that having more accessible neighborhood services was related to lower risks of neglect, even while controlling for receipt of services. A study based in Los Angeles County, California, found that parents residing closer to mental health and substance abuse services reported fewer neglectful behaviors (Maguire-Jack & Klein, 2015). All these studies suggest that community service provisions may have in general protective impacts on overall community CMR rates. However, research that focuses exclusively on EHV provisions and their impacts on CMR rates at a community level is sparse. In addition, prior studies have been conducted within a single-county or single-state setting, which limits generalizability and implications for national policies.

Current Study

To address the gaps in the research, this study examines the association between county EHV provisions and county CMR rates in the United States from 2016 to 2018. We assess two different kinds of EHV provisions: (1) EHV provisions funded by the Maternal, Infant, and Early Childhood Home Visiting (MIECHV) program and (2) any EHV provisions, including both MIECHV-funded and non-MIECHV-funded provisions. The first is a subset of the second, and there may be no fundamental difference between MIECHV-funded and non-MIECHV-funded EHV provisions at the practice level as EHV providers often receive funding from multiple sources. We therefore focus mainly on any EHV provisions and expect that the larger set of EHV provisions (i.e., any EHV provisions) will have stronger associations with CMR rates. Nevertheless, we additionally examine MIECHV-funded EHV provisions. This is because MIECHV is the principal federal funding program solely devoted to support EHV services (Fernandes-Alcantara, 2018). Relevant findings may be of particular interest to advocates and lawmakers considering the impact of the MIECHV program.

We examine both *within-effects* and *between-effects* of EHV provisions and their associations with CMR rates. For within-effects, we compare county CMR rates between years with and without EHV provisions to examine whether longitudinal changes in EHV provisions (from absence to presence of provisions, and vice versa) are associated with longitudinal changes in CMR rates. That is, we test the hypothesis that CMR rates decrease in communities after EHV provisions are launched or that CMR rates increase in communities after EHV provisions are stopped. Within-effects examine short-term (1 year) impacts within counties and have more causal implications by handling unobserved inter-county heterogeneity, same as fixed effects (Bell et al., 2019). Between-effects examine overall impacts over the entire study period (3 years) in a broad social spectrum across counties. Specifically, we compare many counties in a cross-sectional manner to examine inter-county differences in CMR rates by EHV provisions. The expected protective impacts suggest that counties with EHV provisions would have lower CMR rates. However, between-effects cannot handle unobserved inter-county heterogeneity, and it is possible that counties with EHV provisions have higher CMR rates due to uncontrolled higher service needs (e.g., poor mental health). For between-effects, therefore, we have no definite hypothesis and our test is exploratory. Examining both within-effects and between-effects strengthens the insights of this study, as it integrates the benefits of both approaches.

We examine associations overall and within subgroups of demographic characteristics (i.e., age, sex, and race/ethnicity) and maltreatment types (i.e., neglect, physical abuse, and sexual abuse). We expect that associations are stronger among children aged 0-5 than among older children as EHV programs target children aged 0-5. For other subgroups, we have no expectations and our tests are exploratory. We further examine whether associations differ by urbanicity as prior research suggests that risk and protective contexts for child maltreatment can substantially differ between urban and rural areas (Maguire-Jack & Kim, 2021).

This study examines these associations while controlling for potential community-level confounders. Prior studies have identified a range of community risk and protective factors (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014a). Substantial evidence supports that lower socioeconomic conditions are related to increased child maltreatment risk. Regarding demographic factors, emerging evidence suggests that having more racial/ethnic minorities (e.g., Latino or foreign-born residents) may be protective against child maltreatment due to their cultural protective factors (e.g., strong social supports). Communities with more children and fewer female adults are characterized as having high childcare burden, which may increase child maltreatment risk. Communities with more residential moves may have weaker social ties as residents have less time to establish them, which in turn may increase child maltreatment risk. This study's analysis adjusts for these community conditions.

Methods

Data and Sample

This observational ecological study constructed national county-level data linking CMR data, any EHV data, MIECHV-funded EHV data, and Census data from 2016-2018. Our data had a three-level structure: county-years nested in counties, nested in states.

CMR data were obtained from the National Child Abuse and Neglect Data System Child Files. We used all CMRs (hereafter CMR refers to CMR investigated or assessed by CPS) in the 50 states and DC in fiscal years 2016-2018. We excluded duplicate records (0.03%), fatal cases (0.03%), unborn, missing, and over 17 years child age cases (0.65%), and missing county identifier cases (0.21%). The final data had 10,364,174 children with a CMR in fiscal years 2016-2018, based on unique counts of children every year.

We aggregated these children into county-years to calculate county CMR rates for each year from 2016 to 2018. Child Files suppress counties with < 1,000 CMRs to protect confidentiality. This means that many low-populated, mostly rural counties are suppressed. Among 9,426 county-years from 2016 to 2018 (3,142 counties × 3 years), 7,650 county-years were suppressed and excluded from analysis. This study used 1,776 county-years (18.8% of all county-years), which were nested in 592 counties and 48 states and DC (all Vermont and Wyoming counties were suppressed and excluded). The analysis data included mostly high-populated, urban areas, and 75.6% of U.S. children were residing in the county-years used for analysis. Yet, the analysis data had limited generalizability to many low-populated counties.

All other data were provided at the county level. First, we used the MIECHV state fact sheets for fiscal years 2016-2018, obtained from DHHS. The fact sheets listed counties where MIECHV-served families were residing. Second, we used the list of counties with at least one local agency providing an EHV program(s) in fiscal years 2016-2018, obtained from the National Home Visiting Resource Center (NHVRC). Finally, the data for control variables were obtained from American Community Survey data.

Unit of Analysis

This study's unit of analysis is county-year. Prior research suggests that census tracts and zip codes are good default choices for ecological studies, while counties may be too large to ensure similar experiences among residents (Aron et al., 2010). Nevertheless, we used counties for several reasons. The smallest area unit available in Child Files was county, and prior studies have found that county-level information can be useful to examine contextual differences in child maltreatment (Kim & Drake, 2018; Maguire-Jack, 2014b). More importantly, local agencies may provide EHV programs across the entire county area rather than solely within their neighborhood boundary (Maguire-Jack, 2014b).

Measures

Dependent Variables—We computed county CMR rates (= number of children with a CMR per 1,000 children) each year from 2016-2018. We purposively used all CMRs including both substantiated and unsubstantiated reports. Strong evidence supports this approach by showing that virtually no difference exists between substantiated and unsubstantiated reports in a wide range of child maltreatment outcomes (Kohl et al., 2009). This suggests that using only substantiated reports results in substantial undercounts of child maltreatment incidents while doing little to identify false reports. We computed overall CMR rates, as well as sex-, age-, race/ethnicity-, and type-specific CMR rates (see Table 1). We used a total of 12 dependent variables and estimated separate models for each dependent variable.

Independent Variables—County any-EHV provisions (including both MIECHV-funded and non-MIECHV-funded provisions) were measured on a binary scale (yes/no) indicating whether a county had a local agency providing at least one of EHV programs. Currently, 16 EHV models meet the DHHS criteria and operate in the United States. This study used 15 models for this measurement (Table S1) because one model (i.e., Maternal Infant Health Program) was newly added to the DHHS list of EHV models in 2019 and had no data for the study years (2016-2018).

Any-EHV provisions were measured slightly differently between years. While all 15 models were measured in 2017, the 2016 measures omitted one model and the 2018 measures omitted two models (Table S1). We see this as a minor problem with little influence on our estimates because provisions of these omitted models were very low (< 1% of all local agencies and all families served). We conducted sensitivity analysis by excluding states implementing these omitted programs from analysis (seven states in 2016 and six states in 2018). There was no change in the direction and statistical significance of the results. There were only minor changes in effect sizes. We used all states for the final analysis.

County MIECHV-funded EHV provisions were also measured on a binary scale identifying whether a county had families served by a MIECHV-funded EHV program(s). There was no inconsistency in this measurement between years.

Control Variables—We chose the following control variables from the American Community Survey data: median household income, % of single-parent households with related children, % of Black children among resident children, % of Latino children among resident children, % of foreign-born among residents, % children among residents, % of children with disabilities, and % of residents who moved in 1 year. We also controlled for county urbanicity based on the 2013 USDA Rural-Urban Continuum Codes. We collapsed the original nine categories into three (see Table 1).

Analysis—We used within-between random effects linear models (Bell et al., 2019) to examine how within-effects (i.e., longitudinal changes) and between-effects (i.e., inter-county differences) of EHV provisions were associated with CMR rates. We estimated "any EHV" and "MIECHV-funded EHV" models separately for each of 12 dependent variables (see the Supplement for model equations). We used 1,776 county-years for overall and most subgroup-specific analyses. Among these county-years, we excluded 150 county-years with < 300 Black children from Black-specific analysis and 14 county-years with < 300 Latino children from Latino-specific analysis for reliable counts of reported children. We further excluded 15 county-years from Black-specific analysis and 20 county-years from Latino-specific analysis for missing race/ethnicity-specific median income. A few additional outliers (outside ± 4.5 interquartile range) were excluded for Black- (3 county-years), Latino- (8 county-years), physical abuse- (19 county-years), and sexual abuse-specific (3 county-years) analysis. All models included county and state random effects to handle the nesting of county-years in counties and states. The intraclass correlation coefficient (ICC) values based on a null (no predictor) model indicated that the variance of overall CMR rates was placed 40.9% between counties (county-level ICC = 0.409) and 56.5% between states (state-level ICC = 0.565). The large ICC values empirically supported the inclusion of county and state random effects. We used the *lme4* package in R for analysis. Confidence intervals (CIs) were estimated by a bootstrap method.

Results

Table 1 reports the descriptive statistics. Each year, on average 61.3 per 1,000 children in a county had a CMR. CMR rates were similar across sex but differed by age and race/ethnicity. Younger children had higher rates. Black children had higher rates compared with White and Latino children. Neglect was the most frequent type, followed by physical abuse and sexual abuse. A relatively small number of counties showed changes in any EHV provisions from *Year* to *Year+1* ("2016 to 2017" or "2017 to 2018"). Among pairs of *Year* and *Year+1* observations, most had provision in both years or no provision in both years (83.4%, and 11.7%, respectively). The percentage that had no provision in *Year* but provision in *Year+1* was 3.3%, and 1.6% had provision in *Year* but no provision in *Year+1*. Similarly, changes in MIECHV-funded EHV provisions were not frequent. Most showed consistent no provision (50.9%) or consistent provision (46.8%) in both *Year* and *Year+1*. Only 1.4% showed a change from no provision to provision, and 0.8% showed a change from provision to no provision in *Year* and *Year+1*.

Table 2 reports the model results for overall CMR rates. The within-effect (i.e., longitudinal change) of EHV provision had a significant negative association. That is, when the EHV provision increased from 0 (absence) to 1 (presence) longitudinally, report rates significantly decreased by 2.13 per 1,000 children with no control (the unadjusted model) and 2.21 per 1,000 children with controls (the adjusted model). The within-effect of EHV provision did not significantly differ by urbanicity (Table S2 in the Supplement). We further assessed state and county random slopes of the within-effect of EHV provision and found that both random slopes were not significant (results not shown). This indicated that the within-effect of EHV provision did not significantly differ by state or county.

The between-effect (i.e., inter-county difference) of EHV provision was not significant in both unadjusted and adjusted models (Table 2). That is, there was no significant difference in report rates between counties with and without EHV provisions. This association did not significantly differ by urbanicity (Table S2) or state (results not shown).

The within-effect of MIECHV-funded EHV provision had no significant association in both unadjusted and adjusted models (Table 2). This association did not significantly vary by urbanicity (Table S2), county, or state (results not shown).

The between-effect of MIECHV-funded EHV provision was significant with no control (the unadjusted model in Table 2). That is, with no control, report rates were significantly higher among counties with MIECHV-funded EHV provision than among counties with no such provision. With controls, this association was not significant (the adjusted model in Table 2) and did not significantly differ by urbanicity (Table S2) or state (results not shown).

Table 3 presents the results of subgroup-specific analysis with all controls. The within-effect of EHV provision had a significant negative association with CMR rates among children aged 0-5 and among children aged 6-11, but not among children aged 12-17. After beginning EHV programs, report rates decreased by 2.88 per 1,000 children aged 0-5 and 2.59 per 1,000 children aged 6-11. The within-effect of EHV provision was also significantly associated with decreasing sex-specific report rates. After introducing EHV provisions, report rates lowered by 2.13 per 1,000 male children and 2.24 per 1,000 female children. The within-effect of EHV provision had no significant association with other subgroup-specific report rates. The between-effect of EHV provision, the within-effect of MIECHV-funded EHV provision, and the between-effect of MIECHV-funded EHV provision were not significant for any of the subgroups.

Figure 1 visually assesses the within-effect of EHV provision. It depicts changes in CMR rates by the following four longitudinal trends of EHV provisions from “Year” to

"Year+1" (i.e., 2016-to-2017 or 2017-to-2018): absence-to-absence, absence-to-presence, presence-to-absence, and presence-to-presence. Among 1,184 pairs of "Year" and "Year+1" observations, relatively small numbers of pairs showed the absence-to-presence trend and the presence-to-absence trend of *any* EHV provisions (n = 39 and 19, respectively) and *MIECHV-funded* EHV provisions (n = 17 and 10, respectively). Both the unadjusted means (i.e., simple arithmetic means) and adjusted means (i.e., predicted values by the adjusted models in Table 2) of CMR rates decreased with the increase of *any* EHV provisions (i.e., absence-to-presence) and increased with the decrease of *any* EHV provisions (i.e., presence-to-absence). On the other hand, for all longitudinal trends of *MIECHV-funded* EHV provisions, the unadjusted means of CMR rates increased over time and the adjusted means of CMR rates showed no significant change over time. It is worth to note that for the adjusted means of CMR rates, the absence-to-absence and presence-to-presence prediction lines are flat and overlapped to each other because they are statistically held constant while allowing only the within-effect of EHV provision to vary for prediction lines.

We conducted sensitivity analysis using negative binomial models because some less frequent dependent variables, such as Black, Latino, physical abuse, and sexual abuse report rates, were slightly positively skewed (skewness = 1.3 to 1.5). We maintained our linear model findings as they were consistent with those of negative binomial models. Table S3 in the Supplement reports the coefficients and confidence intervals of the control variables for those interested in the relationships between the controls variables and CMR rates.

Discussion

To our knowledge, this work is the first effort to examine the county-level impacts of EHV provisions on CMR rates. We found that longitudinal changes (i.e., within-effects) of any EHV provisions were significantly associated with CMR rates in U.S. county-level data from 2016 to 2018 when a range of controls were considered. That is, after starting any EHV provisions in communities, their CMR rates decreased. After stopping provisions in communities, their CMR rates increased. This association did not significantly differ by urbanicity, county, or state. This association was significant overall and within male, female, age 0-5, and age 6-11 subgroups, but not significant for other subgroups. The between-effect of any EHV provision and both the within- and between-effects of MIECHV-funded EHV provision were not significant overall or within any of the subgroups.

Within-effects can capture only short-term effects (within 1 year for this study). Some may wonder whether EHV provisions can change county CMR rates within such a short timeframe. However, studies do exist that identify changes in community processes (e.g., collective efficacy) immediately after a few months' training or therapy, as well as after several months follow-up (e.g., Aguilar-Raab et al., 2018; Ohmer, 2016). In addition, intervention effects are generally well identified during and immediately after the intervention. It is also common that intervention effects fade out over time during the post-intervention period (Bailey et al., 2017; van Aar et al., 2017). Therefore, it is possible that community changes occur in a relatively short period of time after changes in EHV provisions.

The significant within-effects of any EHV provisions for children aged 0-5 is expected as the EHV programs target this age group. Yet, the significant finding among children aged 6-11 is a somewhat unexpected, exciting finding. Several speculations are possible for this finding. First, the social processes discussed in the Introduction section might be protective of child maltreatment risk for children in both age groups. Second, the finding can be due to the presence of older siblings (aged 6-11) in the same household of EHV-served younger siblings (aged 0-5). EHV programs are often not limited to first-time parents. The majority of families with a child(ren) have more than one child (Pew Research Center, 2015), and the median interpregnancy interval is 2-2.5 years (Copen et al., 2015). EHV-served families with younger children (aged 0-5) therefore may also have older children (aged 6-11), and thus participation may lower CMR rates among children aged 6-11. Finally, interfamilial interactions between children aged 0-5 and aged 6-11 may be common occurrences in a community (Ellis et al., 1981), which may facilitate spillover effects of EHV programs. While further research is needed to draw implications from this exciting finding, it provides suggestive evidence that EHV provisions have impacts on individuals in a community beyond service participants.

These significant findings on the within-effects of any EHV provisions have several important implications. Within-effects are methodologically equivalent to fixed effects, which can control for unobserved inter-county heterogeneity. The within-effect findings therefore have greater implications for causality than cross-sectional findings. This study's findings also make a contribution to the existing evidence base. Prior research has mostly focused on individual-level impacts of EHV (Avellar & Supplee, 2013; Curry et al., 2018; Levey et al., 2017; MacMillan et al., 2009), and research has been sparse on community-level impacts. The within-effect findings help fill this knowledge gap by confirming the EHV-CMR relationship at the community level. Another implication has to do with prevention efforts. Public health approaches, especially community-based strategies, have become a vital part of prevention efforts for social and public health problems (Graaf & Ratliff, 2018; Merzel & D'Afflitti, 2003), including child maltreatment (Lo & Cho, 2021). This study provides evidence supporting potential benefits of integrating EHV provisions into community-based strategies to reduce child maltreatment incidents and reports at the whole community level.

Some aspects of the within-effects findings need further discussion to understand their limitations and where we can go from here. The first limitation is that the effect sizes we identified are small. This is not surprising for two reasons: 1) Each year, the EHV programs serve only about 1% of young U.S. children (NHVRC, 2019). Considering this low provision, small effect sizes are expected and likely to grow if provision is increased. 2) High child maltreatment rates in the United States are closely related to a range of formidable risk factors (e.g., poverty, crime, mental health, and substance abuse problems). It may be impractical to address them solely by EHV services, which are low-intensity and focus largely on individual-level behavioral changes (Finello et al., 2016; Gomby et al., 1999). Despite this limitation, increasing community EHV provision may be worthwhile given the enormous social and economic burden of child maltreatment, including for example costs of child welfare, health care, criminal justice, special education, productivity losses, and quality of life losses (Peterson et al., 2018). Yet, it may be naïve to hope EHV can be a cure-all. As others have noted, communities should adopt EHV as a part of a comprehensive response to child maltreatment (Fernandes-Alcantara, 2018; Finello et al., 2016; Gomby et al., 1999). The second limitation is that we could not examine long-term mechanisms of the community-level relationship between EHV and CMR because the data were only available for 3 years, from 2016 to 2018. It is entirely possible that some community changes that EHV may promote (e.g., establishing social ties) take a long period of time (Sampson et al., 1999). Home visiting also may have long-term effects (e.g., Olds et al., 1998). More research with a longer timeframe is required to understand how fast community-level changes can occur, how they are accumulated over time, and how long they last. Another limitation is that a relatively small number of counties have shown longitudinal changes in EHV provisions in our data. Although this is simply what has occurred among U.S. counties, this limits the generalizability of our findings. Further research is required to confirm our findings. Given the limited but best-available data, nevertheless, our findings have implications for both counties that have EHV provisions and those that do not. The first group is larger than the second, and our findings support maintaining EHV provision. While a smaller number of counties do not have EHV provisions, they are still a substantial group, and many low-populated counties that were excluded from analysis due to confidentiality restrictions likely also do not have EHV programs, given most are rural. Preventive services are generally less available in rural areas than urban areas (Maguire-Jack & Kim, 2021). In line with this, the overall levels of provisions in our data were higher than the known coverages (about 50% for any EHV and about 33% for MIECHV-funded EHV). Our findings suggest that launching EHV provisions could protect a considerable number of families.

The within-effect of any EHV provision was not significant in any subgroup of race/ ethnicity and maltreatment type. First, it was not significant for any of White, Black, and Latino CMR rates. This was perhaps due to our use of the overall measure of EHV provisions. Even if services are available in a community, accessibility and utilization of services can be widely different between racial/ethnic groups (Allard et al., 2003). Race/ ethnicity-specific measures of EHV provisions may be required to identify the potential impacts of EHV provisions on race/ethnicity-specific CMR rates. Second, the within-effect of any EHV provision was also not significant for neglect, physical abuse, or sexual abuse report rates. It is possible, for example that EHV services focus more on neglect in some communities but physical abuse in other communities, based upon each community’s specific needs. This would explain why the impact of EHV provision is less consistent for type-specific CMR rates than for overall CMR rates across communities. Given the small effect size for overall CMR rates, the impact of EHV provision on type-specific CMR rates may be subtle and thus difficult to detect.

We found that the between-effect of any EHV provision was not significant overall or within any of subgroups. A possible reason is that between-effects are methodologically less rigorous than within-effects. Between-effects are therefore vulnerable to inter-county heterogeneity, especially uncontrolled service needs. We controlled for a range of known community risk factors such as socioeconomic (median household income and % single-parent), demographic (% Black, % Latino, and % foreign-born), residential instability (% moved), and care burden factors (% children among residents and % children with disabilities). However, other important risk factors, such as mental health, substance abuse, and crime, were not adjusted for. Concentration of such problems can increase service needs, as well as child maltreatment incidents and reports in communities. EHV services might be provided more often to communities with higher service needs and thus with higher CMR rates. This might offset the protective between-effect of any EHV provision. A more rigorous approach, such as randomization of communities (e.g., Prinz, 2009), may help address the potential heterogeneity in service needs.

Our findings indicate that neither the within- nor the between-effects of MIECHV-funded EHV provisions were significant. We offer several possible explanations for this with no definitive answer. First, the between-effect of MIECHV-funded EHV provision was not significant perhaps because of the abovementioned heterogeneity in service needs. MIECHV also requires states to provide EHV services in at-risk communities with high rates of adversities, including child maltreatment, based on a statewide needs assessment (Fernandes-Alcantara, 2018). This legislative requirement might mean that MIECHV-funded EHV provisions are more concentrated in high risk communities than EHV provisions funded by other sources. Second, MIECHV appears to have reached maturity prior to the study years in that the program did not grow (DHHS, 2020), and indeed in our data, fewer counties showed longitudinal changes in MIECHV-funded EHV provisions compared with any EHV provisions. This lack of longitudinal change might lead to the non-significant within-effect of MIECHV-funded EHV provision. Third, the MIECHV funding is a relatively small part of the entire funding for EHV programs. Among the families served by EHV programs in 2016-2018, slightly over one quarter were served through MIECHV (NHVRC, 2019). The impacts of EHV provisions might not be identifiable when the focus was limited to such a small subset (i.e., MIECHV-funded EHV provisions). Given that both MIECHV and other funding sources support the same EHV programs, we do not view the non-significant within-effect of MIECHV-funded EHV provisions as evidence that EHV does not affect communities. On the contrary, the significant within-effects of any EHV provisions suggest that expansion of MIECHV is likely to increase overall EHV provisions and thus may have benefits in child maltreatment prevention.

Strengths and Limitations

The use of longitudinal county-level data across most states is a clear strength in our assessment of the potential benefits of community EHV provisions beyond a single-state setting. Our use of within-between random effects models is also a strength. This allows for examining both longitudinal changes (i.e., within-effects) and inter-county differences (i.e., between-effects) of community EHV provisions and their associations with CMR rates.

This study has several limitations that warrant caution in interpreting the results. It was based on CMR rates rather than incident rates. Many child maltreatment incidents are not reported to CPS (Sedlak et al., 2010). Hence caution is warranted in drawing implications for child maltreatment incidents from our findings.

Surveillance bias may affect our findings. Families can be under greater surveillance while participating in EHV programs. This may increase their chance of being reported. However, the best available evidence suggests that surveillance bias may exist, but its impact on report rates is very small (Chaffin & Bard, 2006; Drake et al., 2017). We found that CMR rates significantly *decreased* after EHV provisions despite possible surveillance bias, which would slightly increase report rates after EHV provisions. Surveillance bias therefore cannot nullify the statistical significance of our findings, even if it exists.

While within-effects eliminate time-invariant confounders, our findings are still vulnerable to uncontrolled time-varying confounders. Any conclusions about causality should be drawn with caution. Nevertheless, our approach can be useful for future research, especially when an experimental design is not possible, or the focus is on real-world effectiveness.

This study is limited to the community level. Our analysis does not examine the impact of individual-level EHV participation. Information on overall community-level impacts still has important practical implications for, for example, community-based decision-making, resource allocation, and policy/program implementation for EHV provisions. However, such information has limited theoretical implications for understanding specific mechanisms connecting community EHV provisions to reductions in CMR rates. Future research based on multilevel data (i.e., individual-level EHV participations and community-level EHV provisions) is required to better understand community-level functions of EHV provisions. Constructing multilevel data from national or statewide databases is mostly not feasible due to confidentiality restrictions. Yet, each state's MIECHV evaluation data and local agencies' EHV evaluation data may be usable for multilevel research.

Other limitations have to do with our measurement and estimation of EHV provisions. Our findings are based on a simple absence/presence measure and therefore have little implication for the amount of EHV provisions. Moreover, our analyses estimated the expected change in CMR rates per 1-unit change in EHV provisions for either absence-to-presence (+1) or presence-to-absence (−1) change in EHV provisions. Yet the size (i.e., absolute value) of the change in CMR rates can differ between absence-to-presence and presence-to-absence changes. Future research may examine this interaction. In addition, we examined overall EHV provisions rather than a specific EHV program because our focus was on general common functions of EHV programs. Future studies may consider using more detailed measures of community EHV provision.

Our analysis excluded many low-populated, rural counties due to the confidentiality protections imposed on CMR data. Any conclusions or implications regarding such counties should be drawn with caution. Another limitation is that our analysis did not consider possible spatial autocorrelation between adjacent counties. The state random effect addressed possible violation of independence of observations among counties by location in the same state. However, spatial contiguity between counties apart from their nesting in states might still induce spatial autocorrelation. Future spatial analysis is warranted. Finally, we could only examine short-term impacts because EHV and CMR data were only available for 2016-2018.

Conclusions

This study found significant community-level associations between longitudinal changes (i.e., within-effects) of EHV provisions and CMR rates among U.S. counties from 2016 to 2018. These findings make two principal contributions to the existing evidence base. First, it expands our understanding of the EHV-CMR relationship from the individual level to the community level. Second, it expands the scope of data from a single-state setting to many counties across most states, while generalizability of our data is still limited for many low-populated (mostly rural) counties. For policy and practice, our findings suggest that expanding EHV in all counties is a promising strategy to further reduce CMR rates at the community level. Considering that MIECHV-funded EHV provisions are a small subset of all EHV provisions, community-level impacts of MIECHV should be evaluated within the context of overall EHV provisions. More research is needed to confirm our findings, examine longer-term impacts, establish causality, and support generalization to low-populated, rural areas.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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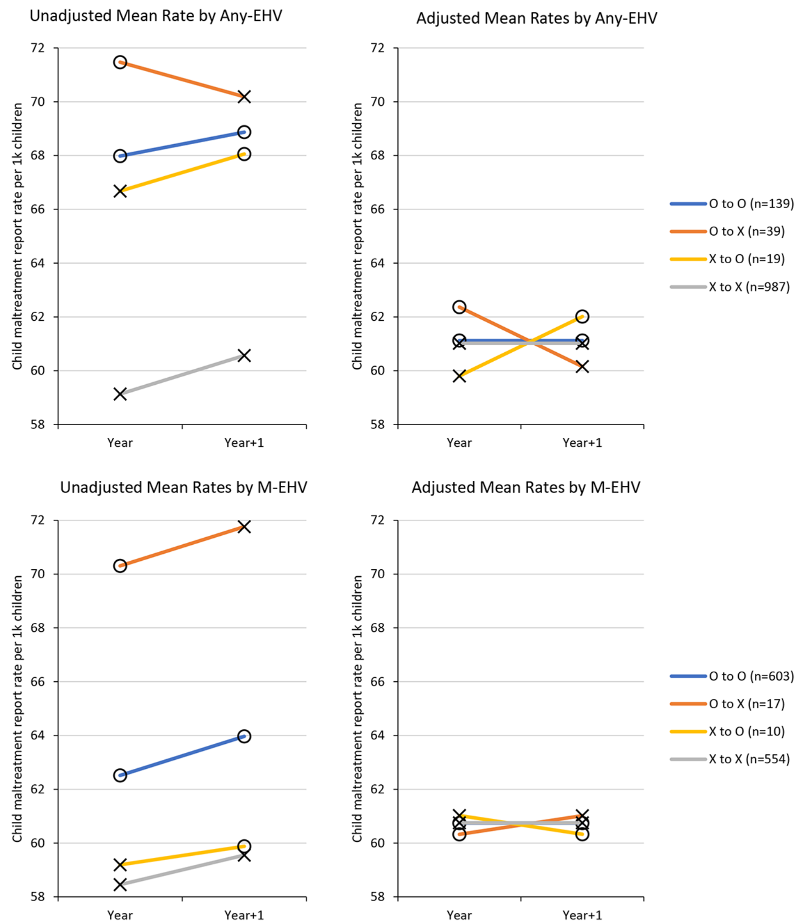

Figure 1. County child maltreatment report rates by absence(O)/presence(X) of EHV provisions.
EHV = evidence-based home visiting. M-EHV = EHV provisions funded by MIECHV (Maternal, Infant, and Early Childhood Home Visiting). Any-EHV includes both M-EHV and non-M-EHV provisions. “Year to Year+1” can be either “2016 to 2017” or “2017 to 2018”. n = the number of “Year” and “Year+1” pairs of county-year observations. For example, 39 pairs of “Year” to “Year+1” (“2016 to 2017” or “2017 to 2018”) showed that any-EHV provisions changed longitudinally from absence(O) to presence(X). Unadjusted mean rates are arithmetic means. Adjusted mean rates are predicted values based on the adjusted models in Table 2 while making the within-effect of EHV provisions vary by the absence/presence status of EHV provisions in “Year” and “Year+1”, but while holding all other variables (including the between-effects of EHV provisions) at their grand means.

Table 1.

Descriptive Statistics, US Counties, 2016-2018

Variable	Mean (SD) or %
Dependent Variables – Child Maltreatment Report Rate	
Total	
Total: # reported per 1k children (N_1=1776; N_2=592; N_3=49)	61.3 (30.4)
By Child Sex	
Male: # reported per 1k male children (N_1=1776; N_2=592; N_3=49)	59.9 (29.7)
Female: # reported per 1k female children (N_1=1776; N_2=592; N_3=49)	61.8 (30.4)
By Child Age	
Age 0-5: # reported per 1k children aged 0-5 years (N_1=1776; N_2=592; N_3=49)	74.5 (39.1)
Age 6-11: # reported per 1k children aged 6-11 years (N_1=1776; N_2=592; N_3=49)	64.0 (31.8)
Age 12-17: # reported per 1k children aged 12-17 years (N_1=1776; N_2=592; N_3=49)	47.3 (23.2)
By Child Race/Ethnicity	
White: # reported per 1k White children (N_1=1776; N_2=592; N_3=49)	51.1 (29.4)
Black: # reported per 1k Black children (N_1=1608; N_2=550; N_3=49)	104.2 (57.0)
Latino: # reported per 1k Hispanic/Latino children (N_1=1734; N_2=586; N_3=49)	47.9 (26.3)
By Maltreatment Type	
Neglect: # reported for neglect per 1k children (N_1=1776; N_2=592; N_3=49)	42.3 (26.0)
Physical abuse (PA): # reported for PA per 1k children (N_1=1757; N_2=586; N_3=49)	13.0 (8.2)
Sexual abuse (SA): # reported for SA per 1k children (N_1=1773; N_2=591; N_3=49)	4.3 (2.9)
Independent Variables (% of pairs of *Year* and *Year+1* observations)	
Changes in any EHV from *Year* to *Year+1* ("2016 to 2017" or "2017 to 2018")	
No provision (0) in both *Year* and *Year+1*	11.7%
No provision (0) in *Year* to provision (1) in *Year+1*	3.3%
Provision (1) in *Year* to no provision (0) in *Year+1*	1.6%
Provision (1) in both *Year* and *Year+1*	83.4%
Changes in MIECHV-funded EHV from *Year* to *Year+1* ("2016 to 2017" or "2017 to 2018")	
No provision (0) in both *Year* and *Year+1*	50.9%
No provision (0) in *Year* to provision (1) in *Year+1*	1.4%
Provision (1) in *Year* to no provision (0) in *Year+1*	0.8%
Provision (1) in both *Year* and *Year+1*	46.8%
Control Variables (based on data for total report rates)	
Median household income per 10k (in 2018 US dollar)	58.0 (14.4)
% single-parent households among resident households with related children	35.6 (7.4)
% Black children among resident children	13.4 (14.3)
% Latino children among resident children	18.4 (17.2)
% foreign-born among residents	8.9 (7.7)
% children among residents	22.9 (3.0)
% children with disabilities among resident children	13.5 (3.1)
% moved in one year among residents	15.3 (3.9)

Variable	Mean (SD) or %
Urbanicity	
Large urban	35.1%
Small urban	52.2%
Rural	12.7%
Year	
2016	33.3%
2017	33.3%
2018	33.3%

Note. N_1 = number of county-year observations. N_2 = number of counties. N_3 = number of states and DC. EHV = evidence-based home visiting. MIECHV = Maternal, Infant, and Early Childhood Home Visiting.

Table 2.

Random Effects Within-Between Models of Child Maltreatment Report Rates per 1,000 Children, U.S. Counties, 2016-2018

	Any EHV models		**MIECHV-funded EHV models**	
	Unadjusted model	**Adjusted model**	**Unadjusted model**	**Adjusted model**
Fixed effects	**Coefficient (95% confidence interval)**			
Any EHV				
Within-effect	**−2.13 (−3.87, −0.58)**	**−2.21 (−3.67, −0.78)**	-	-
Between-effect	−0.31 (−4.97, 4.26)	1.90 (−1.82, 5.36)	-	-
MIECHV-funded EHV				
Within-effect	-	-	0.24 (−2.04, 2.43)	0.69 (−1.66, 3.28)
Between-effect	-	-	**4.15 (0.69, 7.17)**	1.54 (−1.18, 4.34)
Random effects	**Variance**			
Level 1 residual	24.4	23.6	24.5	23.8
Level 2 intercept	288.3	153.0	285.0	152.9
Level 3 intercept	536.0	424.9	541.1	424.3
Model fit	**Bayesian information criterion (BIC)**			
BIC value	13042.3	12763.6	13043.2	12770.3

Note. EHV = evidence-based home visiting provision. MIECHV = Maternal, Infant, and Early Childhood Home Visiting. Sample size = 1,776 county-year observations nested in 592 counties and 48 states and DC. Significant coefficients ($p < .05$) are in boldface. Unadjusted models controlled for year fixed effects, urbanicity, and state and county random intercepts. Adjusted models additionally controlled for within-effects and between-effects of median household income, % single-parent households among households with related children, % Black children among children, % Latino children among children, % foreign-born among residents, % children among residents, % children with disabilities among children, and % moved in one year among residents. A lower Bayesian Information Criterion value indicates a better fit.

Table 3.

Random Effects Within-Between Models of Child Maltreatment Report Rates (CMRR) per 1,000 Children by Age, Sex, Race/Ethnicity (R/E), and Type, U.S. Counties, 2016-2018

	Coefficient (95% confidence interval)					
	Any EHV models			MIECHV-funded EHV models		
Age-specific CMRR	**Age 0-5**	**Age 6-11**	**Age 12-17**	**Age 0-5**	**Age 6-11**	**Age 12-17**
Any EHV						
Within-effect	**−2.88 (−5.17, −0.54)**	**−2.59 (−4.46, −0.61)**	−1.15 (−2.53, 0.31)	-	-	-
Between-effect	2.51 (−2.23, 7.27)	1.23 (−2.52, 5.57)	1.45 (−1.78, 4.57)	-	-	-
MIECHV-funded EHV						
Within-effect	-	-	-	0.68 (−2.46, 3.94)	−0.03 (−2.90, 2.53)	1.70 (−0.30, 3.58)
Between-effect	-	-	-	1.66 (−2.09, 5.26)	1.51 (−1.79, 4.11)	0.88 (−1.59, 3.18)
Sex-specific CMRR	**Male**	**Female**		**Male**	**Female**	
Any EHV						
Within-effect	**−2.13 (−3.82, −0.46)**	**−2.24 (−3.97, −0.47)**		-	-	
Between-effect	2.02 (−1.95, 5.56)	1.58 (−2.32, 5.60)		-	-	
MIECHV-funded EHV						
Within-effect	-	-		0.13 (−2.29, 2.67)	1.17 (−1.40, 3.63)	
Between-effect	-	-		1.54 (−1.36, 4.13)	1.42 (−1.26, 4.43)	
R/E-specific CMRR	**White**	**Black**	**Latino**	**White**	**Black**	**Latino**
Any EHV						
Within-effect	−1.03 (−2.80, 0.70)	−2.44 (−7.93, 2.94)	−1.58 (−4.24, 1.20)	-	-	-
Between-effect	−0.46 (−3.67, 2.96)	7.53 (−4.66, 18.66)	0.26 (−4.70, 4.40)	-	-	-
MIECHV-funded EHV						
Within-effect	-	-	-	0.85 (−1.53, 3.45)	3.47 (−3.14, 10.23)	−0.67 (−4.75, 3.09)
Between-effect	-	-	-	0.31 (−2.18, 2.79)	−2.40 (−10.42, 5.15)	0.01 (−2.84, 3.15)
Type-specific CMRR	**Neglect**	**Physical Abuse**	**Sexual Abuse**	**Neglect**	**Physical Abuse**	**Sexual Abuse**
Any EHV						
Within-effect	−0.84 (−2.23, 0.56)	−0.04 (−0.53, 0.45)	−0.09 (−0.32, 0.13)	-	-	-
Between-effect	2.25 (−0.70, 5.13)	0.42 (−0.87, 1.54)	0.16 (−0.19, 0.50)	-	-	-
MIECHV-funded EHV						

	Coefficient (95% confidence interval)					
	Any EHV models			**MIECHV-funded EHV models**		
Within-effect	-	-	-	0.49 (−1.30, 2.60)	−0.29 (−1.01, 0.38)	0.07 (−0.22, 0.38)
Between-effect	-	-	-	0.89 (−1.45, 3.03)	0.47 (−0.34, 1.26)	0.17 (−0.08, 0.43)

Note. EHV = evidence-based home visiting. MIECHV = Maternal, Infant, and Early Childhood Home Visiting. Table 1 reports the sample size for each model. All models controlled for state and county random intercepts, year fixed effects, urbanicity, as well as within-effects and between-effects of median household income, % single-parent households, % Black children among children, % Latino children among children, % foreign-born among residents, % children among residents, % children with disabilities among children, and % moved in one year among residents. For race/ethnicity-specific models, race/ethnicity-specific measures were used (e.g., White median household income, % single-parent White households, % foreign-born among White residents, % children among White residents, % children with disabilities among White children, and % moved in one year among White residents). Significant coefficients ($p < .05$) are in boldface.