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Longitudinal Changes in the County-Level Relationship between Opioid Prescriptions and Child Maltreatment Reports, United States, 2009-2018

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Abstract

This article examines whether county opioid prescription rates were associated with county child maltreatment report (CMR) rates in the United States and whether this relationship changed over time. We linked multiple national datasets to assemble retail opioid prescription data, CMR data, rural-urban codes (to control for urbanicity), and census data (to control for other community characteristics, such as poverty rates) covering 2009 to 2018. Multilevel linear modeling analyzed the linked data. We found that the strength of the county-level relationship between opioid prescription rates and CMR rates increased almost linearly during the study period. The relationship was not significant in 2009-2011; it became significant in 2012 and grew stronger in the next 6 years. In 2012, there was one more CMR per 1,000 children in a county for every 14.3 more opioid prescriptions per 100 people. In 2018, the number of prescriptions related to this effect was 3.6. In other words, the county-level relationship between opioid prescriptions and CMRs was four times as strong in 2018 as it had been in 2012. This trend was also observed within all subgroups of child age and sex. By type, this trend was somewhat more pronounced for neglect, but somewhat less for sexual abuse. Our findings suggest a growing need for greater efforts to prevent child maltreatment in communities with high opioid prescription rates. Further research is warranted to reveal the underlying factors for this concerning trend.

Keywords

child maltreatment; child abuse and neglect; opioid prescription; community; longitudinal

Introduction

Child maltreatment is a major social and public health problem, posing a heavy societal burden in high-income countries (Gilbert et al., 2009). In 2007, child protective services (CPS) investigated or assessed child maltreatment reports (CMR) concerning 1 in 26 U.S. children (U.S. DHHS, 2012). Due to an upward trend, the number was 1 in 21 U.S. children in 2019 (U.S. DHHS, 2021). Research has identified a range of community risk and protective factors that affect child maltreatment (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014). Emerging evidence suggests that rates of opioid use, misuse,

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and overdose play a significant role at various ecological levels, including census block groups, zip codes, counties, and states (e.g., Bullinger & Ward, 2021; Freisthler et al., 2022; Quast et al., 2018; Wolf et al., 2016). We build on existing research and examine (1) the county-level relationship between opioid prescription rates and CMR rates and (2) the longitudinal change in this relationship.

Opioid Epidemic

The U.S. opioid overdose death rate has increased over seven times, from 2.9 deaths per 100,000 people in 1999 to 21.4 deaths per 100,000 people in 2020 (CDC, 2022). Increased overdose deaths involving prescription opioids drove this upward trend in the 2000s (CDC, 2022). In the 2010s, it became much steeper due to the surge of overdose deaths involving heroin and synthetic opioids (CDC, 2022). The surge of opioid prescriptions due to aggressive and deceitful pharmaceutical marketing is considered one of the main contributors to and even a potential leading cause of the U.S. opioid epidemic (Alpert et al., 2022; DeWeerdt, 2019; Jalali et al., 2020). Although opioid prescription rates have decreased considerably in the United States since 2012 (CDC, 2021), they are still far higher than the rates prior to 1999 and the rates in Europe (Schuchat et al., 2017). To the best of our knowledge the reduction in opioid prescriptions has not yet been linked to a decrease in opioid overdose deaths. Indeed, national rates of prescription opioid overdose deaths remained steady and high in the 2010s while all opioid overdose deaths increased sharply (CDC, 2022).

Prior Research

While this study focuses on opioid prescriptions, this section includes prior studies on the relationships between various indicators of opioid incidents and child maltreatment in an attempt to provide a comprehensive overview. Bullinger and Ward (2021) conducted a study using CMR allegation rates in California counties in 2002-2015 and rates of foster care removals among the 50 U.S. states and DC in 2003-2015. The study found that legal opioid distributions, measured as morphine-equivalent grams per capita, did not have a significant positive association with either of these metrics of child maltreatment. However, a number of other studies have found that higher rates of opioid prescriptions were significantly associated with higher rates of child maltreatment cases, including substantiated CMRs among Tennessee counties in 2006-2016 (Morris et al., 2019), foster care removals among Florida counties in 2012-2015 (Quast et al., 2018), foster care removals among rural California counties in 2009-2016 (Quast et al., 2019), and foster care removals among the counties of 23 U.S. states in 2010-2015 (Quast, 2018).

The relationship between opioid incidents leading to medical attention and child maltreatment cases is consistent across studies. Increased rates of administration of the opioid overdose antidote Naloxone by emergency medical services were related to increased rates of CMRs and substantiated CMRs among Ohio block groups in 2015 (Freisthler et al., 2022). In a majority of U.S. states in 2005-2014, higher rates of opioid-involved emergency department visits correlated with higher rates of foster care removals (Bullinger & Ward, 2021). Higher opioid-involved hospitalization rates were associated with higher rates of CMRs, substantiated CMRs, and foster care removals among U.S. counties

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in 2011-2016 (Ghertner et al., 2018), with higher rates of child maltreatment-involved hospitalizations among Pennsylvania zip codes in 2004-2014 (Sumetsky et al., 2022) and higher rates of child maltreatment/injury-involved hospitalizations among California zip codes in 2001-2011 (Wolf et al., 2016).

Findings on the relationship between opioid-involved deaths and child maltreatment are more inconsistent. A study of the 50 states and DC in 2003-2014 found that rates of foster care removals correlated with opioid-involved death rates (Bullinger & Ward, 2021). Among Washington counties in 2005-2017, rates of opioid overdose hospitalizations and deaths were significantly related to increased rates of CMRs, foster care removals, and child maltreatment-involved hospitalizations without controls; however, with controls, these relationships were not significant (Rebbe et al., 2020). Among California counties in 2002-2015, opioid-involved death rates had no significant positive association with CMR allegation rates (Bullinger & Ward, 2021).

While research on the relationship between the opioid epidemic and child maltreatment has been growing, some important knowledge gaps still exist. First, little research has been done on the relationship between opioid prescriptions and CMRs. Most prior studies focused on opioid-related emergency medical services, hospitalizations, or deaths (Bullinger & Ward, 2021; Freisthler et al., 2022; Ghertner et al., 2018; Rebbe et al., 2020; Sumetsky et al., 2022; Wolf et al., 2016). Some studies examined opioid prescriptions or legal opioid distributions but generally focused on foster care removals (Bullinger & Ward, 2021; Quast, 2018; Quast et al., 2018, 2019). From a public health perspective, understanding the relationship between the opioid epidemic and child maltreatment based on prevalent and early-stage incidents (i.e., opioid prescriptions and CMRs) could inform early prevention efforts that could take place before problems escalate. The two studies examining the relationship between opioid prescriptions and CMRs are limited to a single state setting, California and Tennessee, respectively (Bullinger & Ward, 2021; Morris et al., 2019). Examining this relationship based on national data can help establish generalizability and inform large-scale policies. Finally, many prior studies used data covering multiple years. Yet, none has examined a longitudinal change in the relationship between the opioid epidemic and child maltreatment despite the fact that both the opioid and child maltreatment epidemics in the United States have changed over the last couple of decades. Understanding the longitudinal trend of the relationship between these two factors may be useful for future policy decisions.

Current Study

To help address the gaps in the existing literature, we examine (1) whether the opioid prescription rate is related to the CMR rate at the county level and (2) whether the strength of this relationship has changed over time, using U.S. national county-level data from 2009 to 2018. Specifically, we examine a cross-sectional relationship (i.e., whether counties with higher opioid prescription rates have higher CMR rates than other counties) for each year from 2009 to 2018 and explore whether this relationship has been stable or become stronger or weaker over time. We do not examine whether longitudinal changes of opioid prescription rates predict CMR rates (i.e., whether counties' CMR rates increase over time when their opioid prescription rates increase over time). This is because longitudinal

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changes in these rates are small for most counties (see the Methods section), which would make analysis vulnerable to random fluctuations over time. However, the substantial variations in these rates between counties offer the opportunity to explore the opioid-CMR relationship in diverse ecological contexts, aiding in identification and comprehension of high-risk communities. By focusing on each year's cross-sectional relationship, we can also investigate whether this relationship has strengthened over time. We hypothesize that county opioid prescription rates are related to county CMR rates and that the strength of this relationship differs between years.

We mainly examine overall CMR rates (among all children), but we also assess age-specific CMR rates (among children aged 0-5, 6-11, and 12-17 years), sex-specific CMR rates (among male and female children), and type-specific CMR rates (neglect, physical abuse, and sexual abuse). This is to understand the association between opioid prescription rates and CMR rates for specific child subpopulations and maltreatment types and to assess whether this association is generally consistent across sub-populations and types, rather than to draw firm inferences from formal statistical significance testing. Our examinations for sub-populations and types are therefore largely exploratory, with no specific hypothesis. An area-level analysis like ours cannot use individual-level characteristics (e.g., child age) as an independent variable. At best, for example, % of younger children can be used as an independent variable, but it does not assess the association of opioid prescription rates on younger children's CMRs. We use multiple dependent variables to understand the opioid-CMR relationship for specific sub-populations and types, consistent with prior approaches (Kim & Drake, 2018).

Method

Data

We linked multiple national datasets longitudinally from 2009 to 2018 at the county level. The IRB of the University of Illinois at Urbana-Champaign granted this study exempt status. This section reports how we managed data for analysis, aggregated the child-level CMR data into counties, and linked them with county-level opioid and census data. This section also reports the coverage of the analysis data.

CMR data were obtained from the National Child Abuse and Neglect Data System (NCANDS) Child Files (National Data Archive on Child Abuse and Neglect, n.d.), which contain child-level records of all CMRs that are investigated or assessed by CPS in the 50 U.S. states and DC. We used all CMRs, including both substantiated and unsubstantiated CMRs. Prior research has found similar rates of child maltreatment consequences (e.g., developmental, cognitive, emotional, behavioral, and health problems) and recidivism between substantiated and unsubstantiated CMRs (Hussey et al., 2005; Kohl et al., 2009; Leiter et al., 1994). This suggests that substantiated and unsubstantiated CMRs are both indicators of maltreatment and that substantiation decisions are largely unreliable (Drake, 1996). Substantiated CMRs are a small subset (< 20%) of all CMRs (U.S. DHHS, 2021). Limiting to substantiated CMRs therefore may result in substantial underestimation of child maltreatment rates, while failing to improve specificity by excluding primarily false reports.

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We used all CMRs that were made in the 50 states and DC from 2009 to 2018, which we obtained from the 2009-2019 NCANDS Child Files (the 2019 Child File contained CMRs made in 2018). Among them, we excluded duplicate records (0.06%), records with missing or out-of-range child ages (0.75%), records with suppressed state and county identifiers due to confidentiality protections for fatal cases (0.03%), and records with missing county identifiers (0.29%). We further excluded records in GA 2009-2011, PA 2009-2014, and TN 2009 (1.21%) because these states showed excessive numbers of missing/suppressed records on county identifiers in these years compared to other years, suggesting possible data entry errors. The final child-level data had 31,702,456 children with a CMR in 2009-2018 based on an annual unique count (i.e., counting a child once per year).

To calculate annual CMR rates from 2009 to 2018 for each county, we aggregated the child-level CMR data into county-year observations (county-years). According to the American Community Surveys (ACS; U.S. Census Bureau, 2022), there were about 3,142 counties each year from 2009 to 2018 in the 50 states and DC. Altogether, 31,425 county-years existed (≈ 3,142 counties × 10 years). Among these county-years, we excluded those with no record submission to the NCANDS (i.e., all 53 ND counties in 2009, all 36 OR counties in 2009-2011, three MA counties in 2009-2018, and four RI counties in 2009-2018) and those with the above-mentioned possible entry errors of county identifiers (i.e., all 159 GA counties in 2009-2011, all 67 PA counties in 2009-2014, and all 95 TN counties in 2009). The final county-level longitudinal data covered 96.17% of all county-years in the 50 states and DC from 2009 to 2018.

For confidentiality, the NCANDS suppressed the identifiers of counties with less than 1,000 CMRs per year by replacing the original three-digit identifiers (e.g., 001) with "000." Since the 2-digit state identifiers (e.g., 01) of these suppressed counties were still available, we were able to combine the suppressed counties into a joint county area per state. In the final data, 5,697 county-years were unsuppressed, while 25,349 county-years were suppressed. We combined these suppressed county-years into 456 joint county-years. Among 6,153 (5,697 suppressed + 456 joint) county-years, we excluded 2 county-years due to missing opioid prescription rates. For analysis, we used 6,151 county-years in the 50 states and DC. Combining suppressed counties allowed us to use all data from the suppressed counties (i.e., there was no data loss during this combining process). A drawback was that, in each state, a joint county area represented many low-populated counties, which were mostly rural areas. Yet, large rural counties were unsuppressed, and most states thus had multiple rural counties in the analysis data.

We used county-level data of retail opioid prescriptions each year from 2009 to 2018, obtained from the Centers for Disease Control and Prevention (CDC, 2021). We obtained all control variables, except for urbanicity, from the ACS 5-year estimates (U.S. Census Bureau, 2022). As the 5-year estimates (i.e., average values over 5 years) were centered to mid-year, we linked the ACS 5-year estimates with the CMR and opioid data by mid-year. For example, ACS 2007-2011 was linked to CMR 2009, and ACS 2016-2020 was linked to CMR 2018. Urbanicity data were obtained from the 2013 Rural-Urban Continuum Codes by the U.S. Department of Agriculture (U.S. Department of Agriculture Economic Research Service, 2020). For linkage, the county-years that were suppressed and combined

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in the CMR data were also combined into a joint county-year in the opioid and ACS data while population-weighed means of county-years combined into a joint county-year were assigned.

Measures

We computed the number of children with a CMR per 1,000 children per county each year from 2009 to 2018. Specifically, we measured nine dependent variables (Table 1): one for total CMR rates among all children, three age-specific CMR rates (i.e., rates among children aged 0-5, 6-11, and 12-17 years), two sex-specific CMR rates (i.e., rates among male and female children), and three type-specific CMR rates (i.e., neglect, physical abuse, and sexual abuse report rates among all children). We estimated models separately for each dependent variable.

For the independent variable, we used the number of opioid prescriptions per 100 persons per county each year from 2009 to 2018. The measure included prescriptions of buprenorphine, codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, oxymorphone, propoxyphene, tapentadol, and tramadol, but excluded medications for cough and cold that include opioids and opioid products for treating opioid use disorder (CDC, 2021). In 2017 and on, the opioid data excluded voided or reversed prescriptions, which led to 1.9% fewer opioid prescriptions in 2017-2018 than in earlier years (CDC, 2021). If many voided or reversed opioid prescriptions were concentrated in certain counties in 2017-2018, the opioid-CMR relationship could be altered substantially in these years. However, the small proportion of possibly voided and reversed opioid prescriptions (i.e., 1.9%) might have no considerable influence on the opioid-CMR relationship in 2017-2018.

We adjusted for a range of control variables (Table 1). Prior ecological research on child maltreatment suggests that community impoverishment (e.g., more children in poverty and fewer owner-occupied housing units), child care burden (e.g., more children, more elderly people, more male adults/less female adults, and more children with disabilities), and instability (e.g., more residential moves) increase child maltreatment rates (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014). For race/ethnicity and nativity, some research suggests that higher percentages of Black, Latino, and foreign-born populations may reduce child maltreatment rates (Kim & Drake, 2018; Putnam-Hornstein et al., 2013). Regarding urbanicity, prior research found that CMR rates were much higher in rural areas than urban areas (Maguire-Jack & Kim, 2021). For simplicity, we combined the original nine categories of the USDA codes into three (i.e., code 1 into large urban, codes 2-3 into small urban, and codes 4-9 into rural; see Table 1).

Analysis

We used multilevel linear modeling to estimate the county-level relationship between opioid prescription rates and CMR rates while adjusting for the control variables, using the *lme4* package (version 1.1-30) in R (version 4.2.1). The intra-class correlation coefficient values from our data indicated that 42.7% of the variance in the county CMR rate was between counties, while 50.4% were between states. The remaining variance, less than 7%, was

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situated between county-year observations. This means that CMR rates differed greatly between counties and states but changed little over time in our data. A state random intercept handled the nesting of counties in states. We added year fixed effects (i.e., Y2010, Y2011, …, Y2018; reference year = 2009) to handle multiple observations per county and adjust for the overall CMR trend over time. We added a state-level opioid random slope, which allowed the county-level opioid-CMR relationship to differ by state. While we were mainly interested in overall national relationships rather than state-specific relationships, this practice was empirically sound as adding the random slope significantly improved the model fit. We further added interactions between opioid prescription rates and year fixed effects (i.e., Opioid × Y2010, Opioid × Y2011, …, Opioid × Y2018) to examine how the opioid-CMR relationship in a given year differed from the relationship in the reference year (i.e., 2009). The year-fixed effects and their interactions with opioid prescription rates allowed the models to estimate each year's cross-sectional opioid-CMR relationship from 2009 to 2018. We weighted all estimates by county child populations.

Results

Descriptive statistics

Table 1 reports the descriptive statistics. We weighted the means and standard deviations by county child populations. In 2009, 42.1 per 1,000 children had a CMR per county on average. This CMR rate almost linearly increased each year and reached to 47.9 per 1,000 children in 2018. Overall, 44.8 per 1,000 children had a CMR per county per year on average in 2009-2018. The CMR rate was higher for younger children (i.e., 55.0 per 1,000 children aged 0-5, 45.9 per 1,000 children aged 6-11, and 34.6 per 1,000 children aged 12-17). Male and female children showed similar CMR rates (i.e., 43.6 per 1,000 male children and 45.4 per 1,000 female children). The neglect report rate (i.e., 29.5 per 1,000 children) was the highest, followed by the physical abuse report rate (i.e., 11.0 per 1,000 children) and the sexual abuse report rate (i.e., 3.7 per 1,000 children). All age/sex/type-specific CMR rates, except for the sexual abuse report rate, much showed increasing trends much like the increase in the overall CMR rate. The opioid prescription rate slightly increased from 77.3 per 100 persons in 2009 to 81.0 per 100 persons in 2012. Then, the rate showed an almost linear decrease to 51.7 per 100 persons in 2018. On average, 71.7 opioid prescriptions were made per 100 persons in a county annually in 2009-2018.

Longitudinal Changes in Unadjusted Opioid Coefficients

Table 2 reports the unadjusted opioid coefficients based on linear multilevel models. All models were estimated with no control variable, while including year fixed effects, opioid prescription rates, opioid × year interactions, a state-level random intercept, and a state-level opioid random slope. Each column is based on a separate model on each dependent variable. We report the full model results in Tables S1a–S9a in the Supplement.

The opioid coefficients for each year from 2009 to 2018 in Table 2 were computed based on the opioid main term and the opioid × year interaction terms from the full model results. For total CMR rates, for example, the opioid coefficient in 2009 (0.25) is equal to the opioid main term (0.25 in Table S1a); the opioid coefficient in 2018 (0.63) is the sum of the opioid

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main term (0.25 in Table S1a) and the opioid × year 2018 interaction term (0.38 in Table S1a). The superscript letters indicate the post hoc tests on pairwise comparisons between yearly opioid coefficients (for the details, see the table footnotes). The full results of the post hoc tests are available in Tables S1b–S9b in the Supplement.

With no control, the opioid coefficient on total CMR rates was significant in all years. That is, with no control, the relationship between opioid prescription rates and total CMR rates was significant in all years. For subgroup-specific CMR rates, the opioid coefficients on physical abuse report rates in 2009 and 2010 were not significant. Besides these, the opioid coefficient was significant for all subgroup-specific CMR rates in all years, without controls.

Regarding longitudinal changes, we found that the unadjusted opioid-CMR relationship became stronger in more recent years. The unadjusted opioid coefficient on total CMR rates was 0.25 in 2009. It gradually increased each year, became significantly larger than the 2009 coefficient beginning in 2013, and continued growing to 0.63 in 2018. Similar longitudinal trends were observed for all subgroup-specific CMR rates, except sexual abuse, which also showed an increasing trend in the unadjusted opioid coefficient, but somewhat weaker than others.

Longitudinal Changes in Adjusted Coefficients

Table 3 reports the adjusted opioid coefficients based on linear multilevel models. All models included the control variables, year fixed effects, opioid prescription rates, opioid × year interactions, a state-level random intercept, and a state-level opioid random slope. We report the full model results in Tables S10a–S18a and the full results of the post hoc tests in Tables S10b–S18b in the Supplement.

Adjusting for the control variables revealed that the opioid coefficient was significant in most years, except for those before 2012. As well, the opioid coefficients on physical abuse and sexual abuse report rates were significant only in the last several years (2016-2018 for physical abuse and 2018 for sexual abuse).

We also found that the adjusted opioid-CMR relationship grew stronger over time. The opioid coefficient on total CMR rates increased almost linearly from 0.02 in 2009 to 0.28 in 2018. The coefficient was growing but not significant in 2009-2011. It further grew to 0.07 in 2012 and became significant. Then, it kept growing in significance over time, reaching 0.28 in 2018. That is, in 2012, for every 14.3 (= 1/0.07) more opioid prescriptions per 100 persons in a county, one more child per 1,000 had a CMR. In 2018, 3.6 (= 1/0.28) more opioid prescriptions per 100 persons in a county were related to one more child per 1,000 with a CMR. These findings suggest that the opioid coefficient has increased substantially over time, specifically by 14 times since 2009 and four times since 2012. This strong, increasing trend in the opioid coefficient was also observed in all age- and sex-specific CMR rates. The opioid coefficient on neglect report rates also increased over time. This trend appeared somewhat weaker for physical abuse and the weakest for sexual abuse.

Figure 1 depicts the longitudinal changes in the adjusted opioid coefficients on total and subgroup-specific CMR rates. The opioid coefficients on total, male-specific, and female-

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specific CMR rates showed nearly identical increasing trends as the trend lines are almost completely overlapped in the graph (the top-left panel). The opioid coefficients on age-specific CMR rates also all notably grew over time (the top-right panel). For maltreatment type, the opioid coefficients longitudinally increased the most for neglect, somewhat less for physical abuse, and the least and almost flat for sexual abuse (the bottom-left panel).

To further assess the longitudinal change in the opioid-CMR relationship, Figure 2 depicts predicted county CMR rates by county opioid prescription rates based on the adjusted model in Table 3. In 2009, the relationship was not significant, and the prediction line was also almost flat. In 2018, the relationship was significant, and the prediction line clearly showed that county CMR rates increased (from 39.2 to 96.1 per 1,000 children) along with the increase in the opioid prescription rate (from 0 to 200 per 100 persons).

Discussion

We found that, controlling for potential confounders, the county-level relationship between opioid prescription rates and CMR rates grew substantially and steadily stronger in the United States from 2009 to 2018. This longitudinal growth was found not only for CMR rates among children overall, but also CMR rates within all subgroups of child age and sex. This growth was also identified for all maltreatment subtypes, but more pronounced for neglect and physical abuse than sexual abuse. These findings expand the current evidence base in several ways. First, they contribute to the existing evidence base on the relationship between opioid prescription rates and CMR rates, both of which are prevalent and early-stage problems. This evidence may inform early prevention efforts. Second, ours is the first study examining this relationship based on national longitudinal data covering most U.S. counties in the 2010s, which supports the generalizability of our findings and thus their utility for federal and state policies. Finally, this study reveals for the first time a longitudinal growth in the county-level relationship between opioid prescriptions and CMRs. This trend urges more attention to communities with high rates of opioid prescriptions from professionals specializing in child welfare and protection.

Our study complements two prior studies of community-level relationships between opioid prescriptions and CMRs (Bullinger & Ward, 2021; Morris et al., 2019). Much as Morris et al. (2019) found a significant county-level relationship between opioid prescription rates and substantiated CMR rates among Tennessee counties in 2006-2016, we found a significant relationship between all CMRs (including unsubstantiated reports) in all U.S. counties in 2012-2018. This finding is inconsistent with Bullinger and Ward's (2021) findings at the state level in 2002-2015. This inconsistency might be because Bullinger and Ward (2021) did not consider longitudinal change in the opioid-CMR relationship. We found no significant opioid-CMR relationship at the community level prior to 2012. Thus the 2002-2011 data Bullinger and Ward (2021) considered may be disguising the significant relationship that developed thereafter. Although Morris et al. (2019) also did not consider a longitudinal change in the opioid-CMR relationship in their study of Tennessee counties, its time frame was more recent (i.e., 2006-2016). It is also possible that the significant opioid-CMR relationship that developed across the 50 states and DC at the county level developed earlier in Tennessee counties. The state-level aggregation may have also further

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disguised the opioid-CMR relationship in Bullinger and Ward's (2021) study. More research is required to understand and resolve this inconsistency.

Possible Explanations for the Community-Level Opioid-CMR Relationship

The surge of opioid prescriptions was followed by rises in opioid misuse and addiction, illicit opioid use, and opioid overdose deaths over the last few decades (Califf et al., 2016; Madras, 2017, 2018; Stoicea et al., 2019). Prescription opioids may not necessarily lead to these problems, but exposure to prescription opioids may create the circumstances that lead to them (Bullinger & Ward, 2021; Morris et al., 2019). Such problems may in turn increase the risk of child maltreatment. We discuss several possible explanations for the identified community-level opioid-CMR relationship, even though our data did not allow for empirical testing of them.

First, high supply of prescription opioids in communities may simply increase opioid *use* among parents, which may facilitate opioid *misuse* among parents (Freisthler et al., 2017; Wolf et al., 2016). Such individual-level pathways may compromise parents' cognitive abilities, such as attention to and awareness of child needs, memory capacity, and thinking and decision-making processes (Freisthler et al., 2017; Kepple et al., 2022; Kepple & Freisthler, 2020; Morris et al., 2019). This may in turn increase neglect risk by diminishing parents' capabilities to supervise their children (supervision neglect), meet their children's basic needs (physical neglect), emotionally attach to their children (emotional neglect), and maintain stable environments for their children (environmental neglect; Freisthler et al., 2017; Kepple et al., 2022; Kepple & Freisthler, 2020; Morris et al., 2019; Winstanley & Stover, 2019). Long-term opioid misuse may lead to addiction, which may affect the brain reward system such that parents are less motivated to care for their children but more motivated toward drug-seeking behaviors, which may eventually increase neglect risk (Freisthler et al., 2017; Winstanley & Stover, 2019). More devastating opioid-involved problems, such as overdose, may incapacitate parents such that they cannot physically take care of their children, and hence commit neglect (Kepple & Freisthler, 2020). Some literature also suggests opioid misuse can provoke emotional dysregulation (Winstanley & Stover, 2019), which may increase neglect if it involves depression or physical abuse if it involves anger.

The contextual roles of *social network drug markets*, which are mostly hidden and in which illicit drug sales occur via friend-to-friend networks in communities, are another potential community-level pathway between opioid prescriptions and child maltreatment (Freisthler et al., 2017, p. 245). Higher rates of opioid prescriptions in communities may increase opioid misuse among members of social networks in communities (Freisthler et al., 2017; Morris et al., 2019). This may increase the opportunities to access and misuse opioids among parents within such social networks (Freisthler et al., 2017). Increased opioid misuse in social activities that parents attend may also disorganize social norms and processes of parents' social networks, which may eventually erode collective engagement on vital issues, such as drug abuse, parenting, and child maltreatment (Freisthler et al., 2017; Morris et al., 2019; Ross & Jang, 2000). Increased opioid misuse within parents' social networks may also diminish the availability of dependable caregivers and available resources within the social

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networks for sharing childcare. Protecting their children from misusers may require vigilant supervision by parents (Morris et al., 2019). Both factors are likely to drain parents' energy and resources, which in turn would increase child maltreatment risk (Garbarino & Sherman, 1980).

Routine activity drug markets, in which illicit drug sales between strangers occur on a regular basis and which are usually located in open public places where people gather, also pose a risk (Freisthler et al., 2017). Increased opioid misuse in communities with high rates of opioid prescriptions may diminish social control on drug use (Freisthler et al., 2017; Morris et al., 2019; Wolf et al., 2016) and in turn may attract routine activity drug markets (Freisthler et al., 2017). Such markets may further facilitate parents' access to and misuse of opioids, and such markets may also draw violence (Freisthler et al., 2017). A sociological perspective suggests that communities with a higher level of violence usually have a higher level of fear and distrust among residents. They also show deterioration of positive social processes (e.g., social cohesion, collective efficacy, and collective engagement), which can increase child maltreatment risk in communities (Sampson et al., 1999). From a psychological perspective, problems due to routine activity drug markets, such as drug activities, violence, other drug-facilitated crimes, and overdose deaths, can be environmental stressors for residents, which can increase child maltreatment risk in communities (Belsky, 1993).

In addition to the contextual roles of drug market activities, it is also possible that the opioid epidemic deteriorates community conditions more directly. The opioid epidemic has hit the hardest in vulnerable communities with detrimental conditions, such as low income, low education, low-end occupation, high unemployment, residential instability, and social isolation (DeWeerdt, 2019; Pear et al., 2019; Schell et al., 2022), which are also well-known risk factors for child maltreatment (Coulton et al., 2007; Freisthler et al., 2006; Maguire-Jack, 2014). A national survey found that adults with opioid use disorder often also had substance abuse and mental health disorders (Jones & McCance-Katz, 2019), suggesting higher service and treatment needs in communities with higher rates of opioid use disorder. It is therefore possible that high rates of opioid misuse, addiction, and/or overdose that followed the surge of opioid prescriptions worsen community conditions by aggravating the existing detrimental conditions, diluting community service and treatment resources, and increasing mental health and substance abuse challenges. This in turn can contribute to child maltreatment.

Possible Explanations for the Longitudinal Increase in the Opioid-CMR Relationship

Another finding we could not empirically explain but can speculate about is the longitudinal increase in the community-level relationship between opioid prescription rates and CMR rates. The national trend of opioid overdose deaths indicates that synthetic opioids (which are many times more powerful than traditionally prescribed opioids) and illegal opioids (i.e., heroin and illicitly manufactured synthetic opioids) greatly increased among opioid overdose deaths over the course of the 2010s (CDC, 2022). This suggests users have had an easier transition from traditionally prescribed opioids to synthetic and illicit opioids in more recent years, which might make the community-level relationship between opioid

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prescription rates and CMR rates stronger over time. In another potential explanation, social control might weaken over time, especially in communities with high rates of opioid prescriptions. Lingering social control might have prevented higher opioid prescription rates from increasing CMR rates before 2012. The long-lasting large supplies of prescription opioids in many communities might have deteriorated their social control through *social network drug markets* and *routine activity drug markets* over time, as discussed above. In such contexts, higher opioid prescription rates might more easily increase CMR rates. It is also entirely possible that we are unable to identify the actual reason for the longitudinal increase in the opioid-CMR relationship. While this study controlled for a range of potential time-varying confounders, uncontrolled confounders could explain away the longitudinal change in the opioid-CMR relationship. For example, as Ghertner et al. (2018) pointed out, reporters (e.g., teachers, police officers, doctors, counselors, social workers, family members, friends, and neighborhoods) could become more sensitive to opioid-related problems in more recent years due to the surge of opioid incidents. This might increase the chance of reporting of child maltreatment incidents in more recent years, especially for communities with high opioid prescription rates. Further investigation is necessary to reveal the fundamental factors driving this concerning trend.

Subgroup-Specific Findings

It is worth noting that our analysis of subgroup-specific CMR rates is exploratory in nature, and we do not intend to use these findings as the basis for confirmatory evidence. Rather, they are considered as secondary outcomes. Further studies will be needed to draw firm conclusions.

By maltreatment type, opioid prescription rates tended to have the strongest relationship with neglect report rates, a somewhat weaker relationship with physical abuse report rates, and the weakest relationship with sexual abuse report rates. The longitudinal increases in these relationships also tended to be the largest for neglect, less for physical abuse to some extent, and the least for sexual abuse. Consistently, the individual-level pathways offered in the current child welfare literature mostly suggest the negative influences of parental opioid misuse such as impairment of cognitive functioning, disruption of the brain reward system, and emotional dysregulation increase neglect risk (Freisthler et al., 2017; Kepple et al., 2022; Kepple & Freisthler, 2020; Morris et al., 2019; Winstanley & Stover, 2019). While community-level research on the opioid-CMR relationship by maltreatment type is sparse, prior ecological research on child maltreatment suggests that community disadvantages, such as poverty, household crowding, violent crime, and residential instability, had stronger relationships with neglect than with other maltreatment types (Coulton et al., 2007). More research is needed to understand type-specific mechanisms in the opioid-CMR relationship.

There was no considerable difference by child sex in either the opioid-CMR relationship or its longitudinal change. There was also no notable difference by child age. Further research is necessary to confirm and better understand subgroup-specific relationships.

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Strengths and Limitations

The strengths of this study are related to its data and analytic approach. The use of administrative data allowed us to construct national longitudinal data covering almost all U.S. counties from 2009 to 2018. The county-level data construction also allowed us to link opioid prescription data with CMR data, which would be impossible at the individual level. By using multilevel modeling, we could examine the county-level relationship between the opioid prescription rate and the CMR rate while properly handling state-level variations in both the CMR rate and the county-level relationship.

This study has several limitations, which call for caution in interpreting its findings. First, our study design is observational, which limits our ability to draw firm causal inferences from our findings and the causal inferences we make are purely speculative. Second, we primarily modeled the cross-sectional relationship between opioid prescription rates and CMR rates across counties for each year. Although this enabled us to investigate longitudinal shifts in this cross-sectional relationship, future research may explore other longitudinal dimensions, for example by modeling longitudinal relationships and time-lagged effects. Third, we present county-level findings. Future individual-level research could confirm our findings at that level. Our county-level findings also have limited implications for smaller area units (e.g., tracts and zip codes). Although prior research suggests that county-level findings can be useful to understand ecological contexts of child maltreatment (e.g., Ghertner et al., 2018; Kim & Drake, 2018; Maguire-Jack & Kim, 2021; Morris et al., 2019), smaller area units may ensure more homogeneous contextual experiences among residents (Aron et al., 2010). Fourth, this study focuses on child maltreatment incidents that were reported to CPS, rather than all incidents. Caution is warranted when drawing implications for unreported incidents. Fifth, several limitations are related to the measurement of the independent variable. While national opioid prescription data were available and used in analysis, no data were available for illicit opioids (e.g., heroin and unlawfully manufactured fentanyl). More research on the relationship between illicit opioids and child maltreatment is warranted given the rapid increase in problems related to illegal opioids (CDC, 2022). The measurement of opioid prescription rates was also limited to simple counts of prescriptions with no information for the amount of opioids in each prescription. Another limitation is that we could not control for the rates of other substance use (e.g., alcohol and other drugs) due to the lack of available data. Future research may consider other substances to understand the unique contributions of opioids. Finally, a prior study found that the relationship between opioid prescription rates and foster care removal rates significantly varied by state (Quast, 2018). We also identified a significant between-state variation in the relationship between opioid prescription rates and CMR rates. While we considered this between-state variation in modeling (i.e., a state-level opioid random slope), our focus was mainly on the overall national relationship. Future studies may focus on the between-state variation.

Implications

This study has implications for theory, research, and policy and practice. With regard to theory, to the best of our knowledge, ours is the first work that confirms the county-level relationship between opioid prescription rates and CMR rates, using U.S. national data. This

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finding adds to the nascent evidence base on the relationship between opioid prescriptions and CMRs. More importantly, this finding establishes the generalizability of this relationship across the nation, which provides empirical support for federal-level efforts. This study also reveals that this relationship intensified over the 2010s. This is important new knowledge, suggesting the urgency of further research and efforts to better understand and reverse this concerning trend.

For research, this study provides groundwork for future investigations of the specific mechanisms underlying the opioid-CMR relationship and its longitudinal growth. This study also highlights additional data needs. Gathering data on opioid prescriptions and CMRs at a smaller geographic scale, such as zip codes and tracts, would allow us to broaden the scope of our findings and identify specific regions that require focused interventions. Although it may not be possible to collect opioid prescription and CMR data for the entire nation at a more specific geographic level, it is feasible to compile statewide data through the use of state Prescription Drug Monitoring Program records and state CPS records. Another potential avenue to explore is integrating child welfare, medical, criminal, and other administrative records by state. This would enable the analysis and monitoring of a range of indicators related to child maltreatment and opioid use, including CMRs, medical records of child maltreatment incidents, opioid prescriptions, and medical and criminal records of opioid use, misuse, abuse, overdose, and illicit use. Collectively, this line of work promises to improve our comprehension of issues related to opioids and child maltreatment, with increased precision and depth, thereby offering valuable insights to prevent and mitigate incidents and reports of child maltreatment.

For policy and practice, our findings suggest that high rates of opioid prescriptions can be included in the list of community risk factors for CMRs. Concentrations of social problems, such as poverty, domestic violence, crime, and substance abuse, are used to identify communities at high risk of child maltreatment and allocate prevention resources across communities (Daley et al., 2016; Fernandes-Alcantara, 2018). As the association between opioid prescription rates and child maltreatment report rates becomes increasingly robust over time, it is imperative to factor in opioid prescription rates in such practices.

This study also calls for better monitoring and flagging strategies that can trigger increased prevention efforts for CMRs. The federal government can invest and develop robust monitoring systems and incentivize states to implement them. States can use the existing Prescription Drug Monitoring Program to flag communities with high opioid prescription rates for intervention. State departments of health, public health, human services, and child welfare can collaborate to assess child maltreatment risk and enhance efforts for parenting and child safety in these communities. For example, states can use existing administrative records (e.g., medical and CPS records) to monitor community child maltreatment risk (Fallon et al., 2010; Schnitzer et al., 2011). States can also attempt to identify child maltreatment incidents hidden from administrative records by conducting surveys on community professionals working with children and their families (Fallon et al., 2010) or on community children (Finkelhor et al., 2015). To strengthen efforts to prevent child maltreatment, states can implement community-based interventions that focus on improving neighborhood processes (e.g., social cohesion, social control, and collective efficacy; van

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Dijken et al., 2016) and/or evidence-based interventions, such as evidence-based home visiting programs and the Positive Parenting Program (Triple P) system (Kim et al., 2022; MacMillan et al., 2009; Prinz et al., 2009).

To the degree causal mechanisms operate in the identified relationship and its longitudinal growth, our findings may suggest increased importance of preventing excessive opioid prescriptions and intervening in their negative impacts on communities (e.g., increased rates of misuse and use disorders, increased drug market activities, and deteriorated positive social processes) to reduce CMRs. Interventions can focus on individuals, such as physicians and parental patients, through for example developing guidelines on opioid prescribing and use, promoting public awareness campaigns, and distributing educational resources (Quast, 2018). Policy-wise, states can consider mandatory use of Prescription Drug Monitoring Programs to reduce unnecessary opioid prescriptions (Morris et al., 2019). Although these efforts may reduce prescription opioids in communities, past experiences suggest that reducing the supply of prescription opioids may increase the supply of illicit opioids and other illicit drugs in communities (Freisthler et al., 2022). A more holistic, strength-based approach at the community level may be required. As Freisthler et al. (2022) suggest, for example, multidisciplinary rapid response teams (including professionals from health, public health, social work, and other disciplines) can be deployed to communities with high rates of opioid prescriptions in order to help restore positive social processes (e.g., social cohesion and control) and reduce opioid-related harms in communities. Our findings suggest the urgency and growing importance of these efforts at the federal level, while further research is required for firm conclusions.

Conclusions

Substance abuse is one of the main risk factors of child maltreatment. Given the severity of opioid and child maltreatment epidemics across U.S. communities, gaining a deeper understand of the relationship between these devasting problems has important implications for both knowledge and practice. This study is one of the earliest to examine a longitudinal change in the county-level relationship between opioid prescription rates and CMR rates across most U.S. counties. The findings suggest that this relationship may have grown stronger over the last decade. Further research is required to confirm these nascent findings and illuminate their underlying mechanisms to further inform policy interventions.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Public Policy Relevance Statements:

This study confirms the county-level relationship between opioid prescription rates and CMR rates across the United States, providing empirical support for federal efforts to address CMR. The relationship intensified over the 2010s, highlighting the urgency of further research and efforts to better understand and reverse this trend. Policy and practice should factor in opioid prescription rates and implement better monitoring and prevention strategies, and holistic, strength-based approaches at the community level may be necessary to reduce opioid-related harms and child maltreatment incidents and reports.

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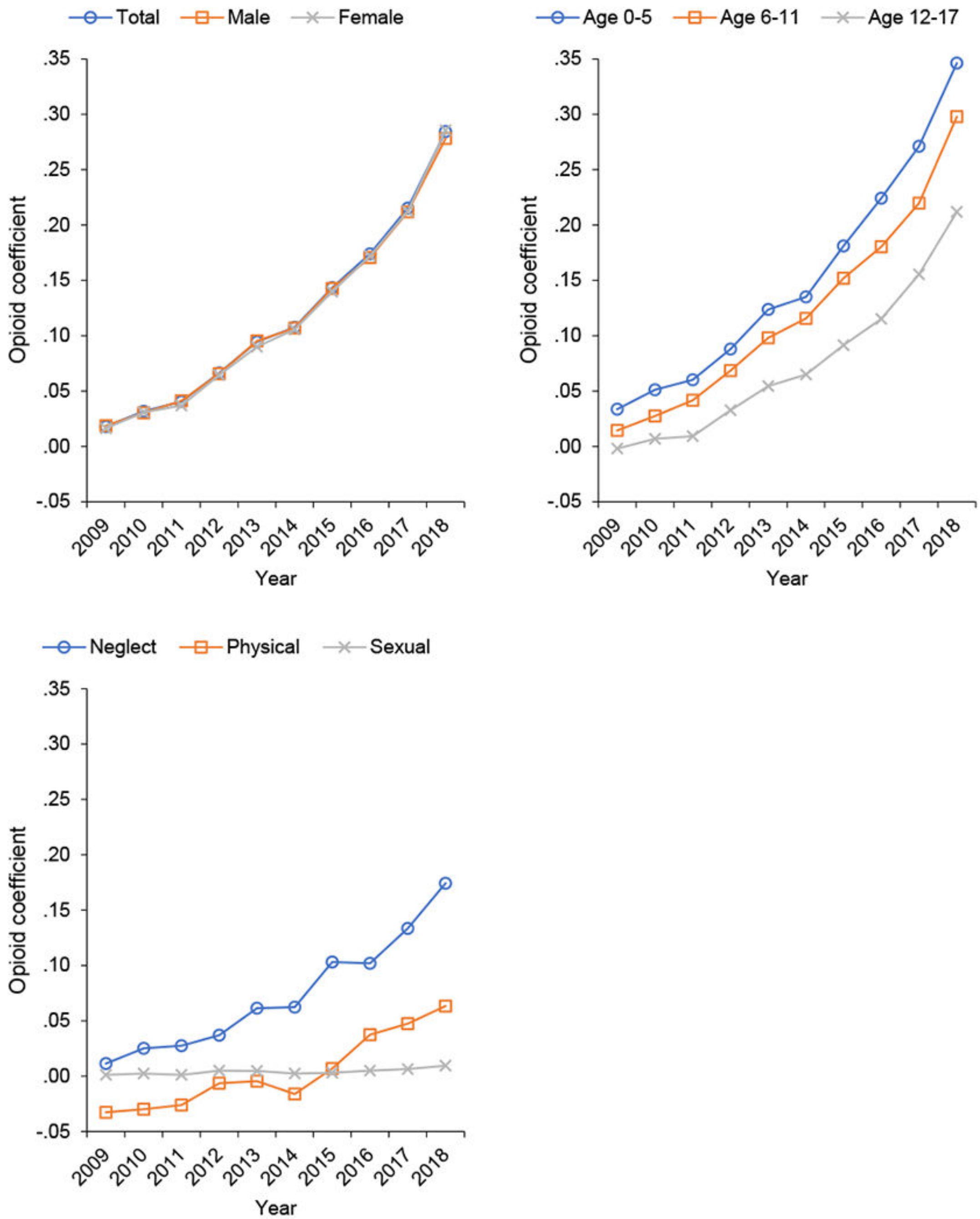

Figure 1.

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

Note. The adjusted coefficients are based on the yearly opioid coefficients in Table 3.

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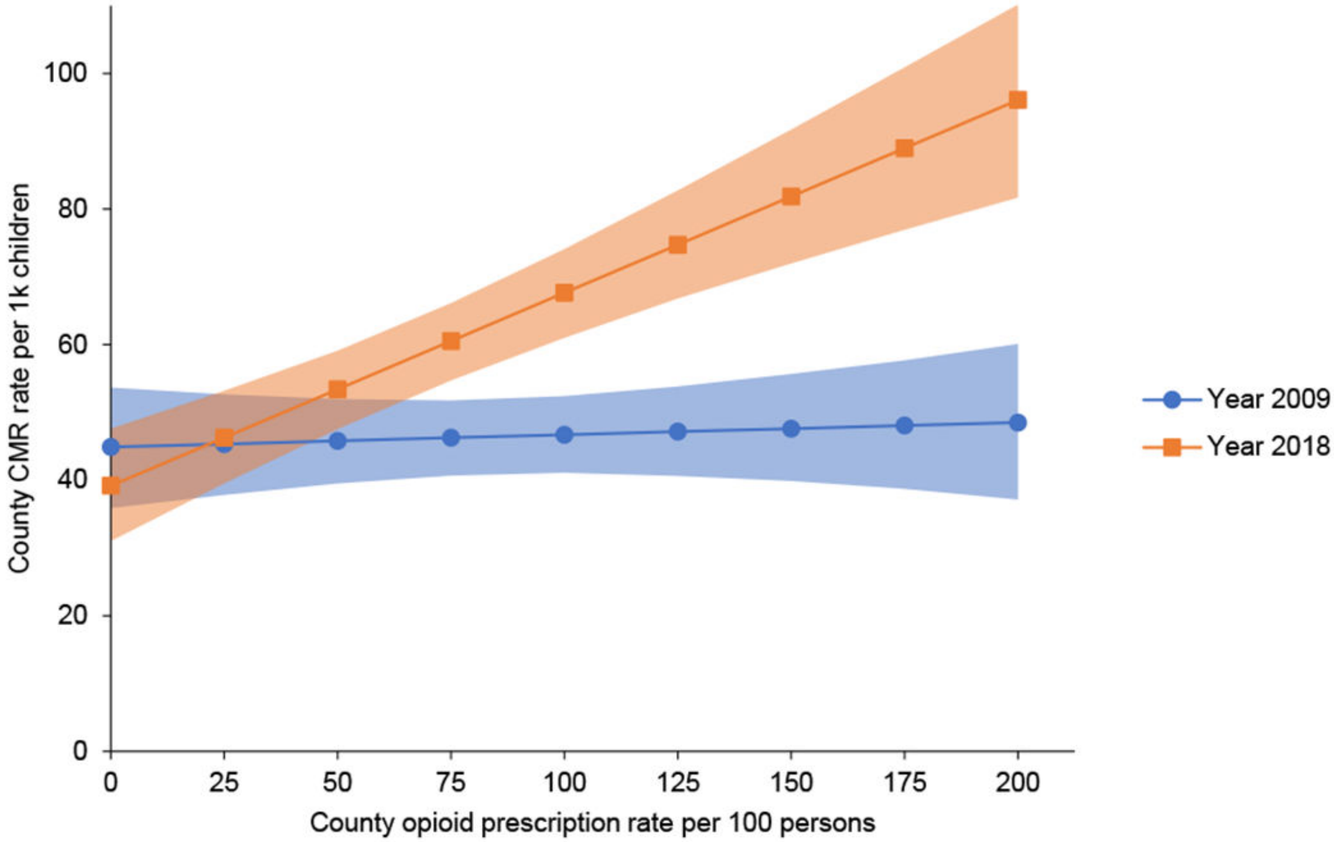

Figure 2.

Predicted county total child maltreatment report rates by county opioid prescription rates in 2009 and 2018, U.S. counties.

Note. The prediction lines are based on the adjusted model on total CMR rates in Table 3.

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Table 1.

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

	M or % in Each Year										
Variables	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**M (SD) or % in 2009-2018**
Dependent Variables											
Total: # reported per 1k children	42.1	42.6	43.4	43.9	43.7	45.3	45.0	46.3	47.1	47.9	44.8 (21.4)
Age 0-5: # reported per 1k children aged 0-5	52.6	53.7	54.8	55.2	54.7	55.7	54.5	55.8	56.2	56.6	55.0 (27.8)
Age 6-11: # reported per 1k children aged 6-11	42.1	42.6	43.3	44.2	44.3	46.6	46.8	48.4	49.2	50.2	45.9 (22.0)
Age 12-17: # reported per 1k children aged 12-17	32.5	32.6	33.1	33.3	33.2	34.7	34.8	36.0	36.9	38.0	34.6 (16.7)
Male: # reported per 1k male children	40.7	41.3	42.2	42.8	42.7	44.3	43.9	45.2	45.8	46.6	43.6 (21.0)
Female: # reported per 1k female children	43.0	43.5	44.2	44.6	44.3	45.9	45.5	46.8	47.7	48.5	45.4 (21.5)
Neglect: # reported for neglect per 1k children	27.8	28.6	29.0	28.8	28.9	29.8	29.6	30.0	30.8	31.3	29.5 (18.1)
Physical: # reported for PA per 1k children	10.3	10.7	10.8	10.8	10.6	10.6	11.0	11.7	11.7	11.8	11.0 (7.2)
Sexual: # reported for SA per 1k children	3.7	3.8	3.7	3.7	3.6	3.5	3.5	3.6	3.7	3.9	3.7 (2.4)
Independent Variables											
Opioid prescription rate per 100 persons	77.3	80.3	80.1	81.0	77.8	75.3	70.5	66.5	59.2	51.7	71.7 (28.4)
Control Variables											
% children in poverty	19.9	20.9	21.6	22.0	21.8	21.3	20.3	19.5	18.5	17.5	20.3 (7.3)
% children aged 0-5 in poverty	22.6	23.7	24.4	24.7	24.3	23.5	22.3	21.3	20.1	18.9	22.5 (8.1)
% children aged 6-11 in poverty	19.8	20.8	21.6	22.1	22.1	21.6	20.7	20.0	19.0	18.0	20.6 (7.6)
% children aged 12-17 in poverty	17.4	18.2	18.9	19.4	19.3	18.8	18.1	17.4	16.6	15.8	18.0 (6.7)
% owner occupied housing units	65.9	65.3	64.7	64.1	63.6	63.3	63.7	63.8	63.9	64.3	64.2 (10.1)
% Black among children	13.9	13.9	13.8	14.3	14.2	14.2	14.1	14.1	14.0	13.9	14.1 (13.3)
% Latino among children	24.0	24.1	24.5	24.4	24.6	24.9	24.7	25.0	25.2	25.2	24.7 (20.0)
% foreign-born among persons	13.6	13.4	13.5	13.4	13.5	13.6	13.5	13.5	13.6	13.6	13.5 (10.7)
% children among persons	24.5	24.3	24.1	23.9	23.7	23.5	23.2	23.1	22.9	22.8	23.6 (2.7)
% elderly (≥ age 65) among persons	12.7	12.9	13.2	13.4	13.8	14.2	14.6	15.0	15.4	15.8	14.1 (3.3)
% male among adults aged 20-64 years	49.6	49.6	49.7	49.6	49.7	49.7	49.7	49.7	49.7	49.8	49.7 (1.2)
% with disabilities among children	3.9	4.0	4.0	4.0	4.1	4.1	4.2	4.2	4.2	4.3	4.1 (1.1)
% moved in one year among persons	15.5	15.3	15.2	15.2	15.0	14.9	14.6	14.5	14.2	13.8	14.8 (3.3)
Large urban (metro area with ≥ 1 million population)	32.0%	31.8%	31.8%	32.5%	32.5%	32.5%	32.7%	32.7%	32.8%	32.8%	32.4%

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	M or % in Each Year										
Variables	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**M (SD) or % in 2009-2018**
Small urban (metro area with < 1 million population)	50.2%	50.2%	50.2%	49.1%	49.1%	49.1%	49.3%	49.3%	49.4%	49.4%	49.5%
Rural (nonmetro area)	17.9%	18.0%	18.0%	18.3%	18.3%	18.3%	18.0%	18.0%	17.9%	17.9%	18.1%

Note. N = 6,151 county-years.

M = mean.

SD = standard deviation.

PA = physical abuse.

SA = sexual abuse.

Means (M) and standard deviations (SD) are weighted by county child populations.

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Table 2.

Unadjusted Coefficients of County Opioid Prescription Rates on County Child Maltreatment Report (CMR) Rates by Year, U.S. Counties, 2009-2018.

	Opioid coefficient (standard error)								
	Total CMR rate	Age-specific CMR rate			Sex-specific CMR rate		Type-specific CMR rate		
Year	**Model 1: CMR rate among all children (N=6,151)**	**Model 2: CMR rate among age 0-5 children (N=6,151)**	**Model 3: CMR rate among age 6-11 children (N=6,151)**	**Model 4: CMR rate among age 12-17 children (N=6,151)**	**Model 5: CMR rate among male children (N=6,151)**	**Model 6: CMR rate among female children (N=6,151)**	**Model 7: Neglect report rate among all children (N=6,151)**	**Model 8: Physical abuse report rate among all children (N=6,151)**	**Model 9: Sexual abuse report rate among all children (N=6,151)**
2009	**.25** (.02)	**.42** (.03)	**.24** (.02)	**.12** (.02)	**.25** (.02)	**.26** (.02)	**.22** (.02)	.01 (.01)	**.02** (.002)
2010	**.27** (.02)	**.43** (.02)	**.25** (.02)	**.13** (.02)	**.26** (.02)	**.27** (.02)	**.24** (.02)	.01 (.01)	**.02** (.002)
2011	**.28** (.02)	**.45** (.02)	**.27** (.02)	**.13** (.02)	**.27** (.02)	**.28** (.02)	**.24** (.02)	**.02** (.01)	**.02** (.002)
2012	**.30** (.02)	**.47** (.02)	**.29** (.02)	**.16** (.01)	**.30** (.02)	**.31** (.02)	**.25** (.02)	**.04** (.01)	**.03** (.002)
2013	**.34** (.02)^{a}	**.53** (.02)^{a}	**.33** (.02)^{a}	**.19** (.02)	**.34** (.02)^{a}	**.34** (.02)^{a}	**.28** (.02)	**.04** (.01)^{ab}	**.03** (.002)
2014	**.37** (.02)^{abc}	**.56** (.03)^{abc}	**.37** (.02)^{abc}	**.21** (.02)^{abc}	**.36** (.02)^{abc}	**.37** (.02)^{abc}	**.30** (.02)^{a}	**.04** (.01)	**.03** (.002)
2015	**.42** (.02)^{abcd}	**.63** (.03)^{abcd}	**.42** (.02)^{abcd}	**.24** (.02)^{abcd}	**.42** (.02)^{abcd}	**.42** (.02)^{abcd}	**.36** (.02)^{abcde}	**.06** (.01)^{abc}	**.03** (.002)
2016	**.47** (.02)^{abcdef}	**.70** (.03)^{abcdef}	**.46** (.02)^{abcdef}	**.27** (.02)^{abcde}	**.46** (.02)^{abcdef}	**.48** (.02)^{abcdef}	**.37** (.02)^{abcdef}	**.10** (.01)^{abcdefg}	**.03** (.002)
2017	**.54** (.03)^{abcdefg}	**.80** (.03)^{abcdefg}	**.53** (.03)^{abcdefg}	**.33** (.02)^{abcdefg}	**.53** (.02)^{abcdefg}	**.54** (.03)^{abcdefg}	**.43** (.02)^{abcdef}	**.12** (.01)^{abcdefg}	**.03** (.003)^{abc}
2018	**.63** (.03)^{abcdefgh}	**.92** (.04)^{abcdefgh}	**.62** (.03)^{abcdefgh}	**.39** (.02)^{abcdefgh}	**.62** (.03)^{abcdefgh}	**.64** (.03)^{abcdefgh}	**.50** (.02)^{abcdefgh}	**.14** (.01)^{abcdefg}	**.04** (.003)^{abcdefg}

Note. N = 6,151 county-years for all models. Each column (i.e., each dependent variable) was estimated by a separate linear multilevel model that included a state-level random intercept, a state-level random slope of the opioid prescription rate, year fixed effects, a main term of the opioid prescription rate, and opioid × year interaction terms. Each year's opioid coefficient in this table was computed by the sum of the opioid main term and the opioid × year interaction term. Full model results of Models 1-9 are available in supplementary Tables S1a–S9a. The results of the post hoc tests on pairwise comparisons between yearly opioid coefficients are reported by superscript letters in this table. Full results of the post hoc tests are available in supplementary Tables S1b–S9b. All estimates were weighted by county child populations.

Significant opioid coefficients (i.e., significantly different from 0 at p<.05) are in boldface.

$^{a\text{-}h}$The opioid coefficient in the given year is significantly different from the opioid coefficient in 2009^{a}, 2010^{b}, 2011^{c}, 2012^{d}, 2013^{e}, 2014^{f}, 2015^{g}, or 2016^{h} at p<.05 (adjusted by Tukey's method).

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Table 3.

Adjusted Coefficients of County Opioid Prescription Rates on County Child Maltreatment Report (CMR) Rates by Year, U.S. Counties, 2009-2018.

	Opioid coefficient (standard error)								
	Total CMR rate	**Age-specific CMR rate**			**Sex-specific CMR rate**		**Type-specific CMR rate**		
Year	**Model 10: CMR rate among all children (N=6,151)**	**Model 11: CMR rate among age 0-5 children (N=6,151)**	**Model 12: CMR rate among age 6-11 children (N=6,151)**	**Model 13: CMR rate among age 12-17 children (N=6,151)**	**Model 14: CMR rate among male children (N=6,151)**	**Model 15: CMR rate among female children (N=6,151)**	**Model 16: Neglect report rate among all children (N=6,151)**	**Model 17: Physical abuse report rate among all children (N=6,151)**	**Model 18: Sexual abuse report rate among all children (N=6,151)**
2009	.02 (.03)	.03 (.04)	.01 (.04)	.00 (.03)	.02 (.03)	.02 (.03)	.01 (.03)	−.03 (.02)	.00 (.004)
2010	.03 (.03)	.05 (.04)	.03 (.03)	.01 (.03)	.03 (.03)	.03 (.03)	.03 (.03)	−.03 (.02)	.00 (.004)
2011	.04 (.03)	.06 (.04)	.04 (.03)	.01 (.03)	.04 (.03)	.04 (.03)	.03 (.03)	−.03 (.02)	.00 (.004)
2012	**.07** (.03)	**.09** (.04)	**.07** (.03)	.03 (.03)	**.07** (.03)	.06 (.03)	.04 (.03)	−.01 (.02)[a]	.01 (.004)
2013	**.09** (.03)[ab]	**.12** (.04)[a]	**.10** (.03)[ab]	**.05** (.03)[a]	**.10** (.03)[ab]	**.09** (.03)[a]	**.06** (.03)	.00 (.02)[ab]	.00 (.004)
2014	**.11** (.03)[abc]	**.14** (.04)[ab]	**.12** (.03)[abc]	**.07** (.03)[abc]	**.11** (.03)[abc]	**.11** (.03)[abc]	**.06** (.03)	−.02 (.02)	.00 (.004)
2015	**.14** (.03)[abcd]	**.18** (.04)[abcd]	**.15** (.04)[abcd]	**.09** (.03)[abcd]	**.14** (.03)[abcd]	**.14** (.03)[abcd]	**.10** (.03)[abcd]	.01 (.02)[abc]	.00 (.004)
2016	**.17** (.03)[abcde]	**.22** (.04)[abcdef]	**.18** (.04)[abcde]	**.12** (.03)[abcde]	**.17** (.03)[abcde]	**.17** (.03)[abcde]	**.10** (.03)[abcd]	**.04** (.02)[abcdef]	.01 (.004)
2017	**.22** (.04)[abcdef]	**.27** (.05)[abcdef]	**.22** (.04)[abcdef]	**.16** (.03)[abcdefg]	**.21** (.04)[abcdef]	**.21** (.04)[abcdef]	**.13** (.03)[abcdef]	**.05** (.02)[abcdefg]	.01 (.004)
2018	**.28** (.04)[abcdefgh]	**.35** (.05)[abcdefgh]	**.30** (.04)[abcdefgh]	**.21** (.03)[abcdefgh]	**.28** (.04)[abcdefgh]	**.29** (.04)[abcdefgh]	**.17** (.03)[abcdefgh]	**.06** (.02)[abcdefg]	**.01** (.004)

Note. N = 6,151 county-years for all models. Each column (i.e., each dependent variable) was estimated by a separate linear multilevel model that included a state-level random intercept, a state-level random slope of the opioid prescription rate, year fixed effects, a main term of the opioid prescription rate, opioid × year interaction terms, and the following control variables: % children in poverty, % owner-occupied housing units, % Black among children, % Latino among children, % foreign-born among persons, % children among persons, % elderly (≥ age 65) among persons, % male among adults aged 20-64, % with disabilities among children, % moved in one year among persons, and urbanicity. Each year's opioid coefficient in this table was computed by the sum of the opioid main term and the opioid × year interaction term. Full model results of Models 10-18 are available in supplementary Tables S10a–S18a. The results of the post hoc tests on pairwise comparisons between yearly opioid coefficients are reported by superscript letters in this table. Full results of the post hoc tests are available in supplementary Tables S10b–S18b. All estimates were weighted by county child populations.

Significant opioid coefficients (i.e., significantly different from 0 at p<.05) are in boldface.

[a-h]The opioid coefficient in the given year is significantly different from the opioid coefficient in 2009[a], 2010[b], 2011[c], 2012[d], 2013[e], 2014[f], 2015[g], or 2016[h] at p<.05 (adjusted by Tukey's method).