NBER WORKING PAPER SERIES

TEMPERATURE AND MALTREATMENT OF YOUNG CHILDREN

Mary F. Evans
Ludovica Gazze
Jessamyn Schaller

Working Paper 31522
http://www.nber.org/papers/w31522

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2023, Revised October 2024

First version: January 2023. This Version: October 2024. Affiliations: Evans—Lyndon B. Johnson School of Public Affairs, University of Texas at Austin, USA; Gazze—Department of Economics, University of Warwick, UK; Schaller— Robert Day School of Economics and Finance, Claremont McKenna College, USA.We thank anonymous reviewers, Ben Hansen, Jamie Mullins, Ariel Ortiz-Bobea, Jisung R. Park, Jennifer Sorenson Leitner, and Casey Wichman for helpful suggestions; as well as participants at seminars at the University of California Los Angeles, University of Warwick, University of Wisconsin-Madison, University of Oregon, University of Texas at Austin, Indiana University, Loghborough University, Texas A&M University, University of Chicago, Georgia State University, ITAM, University of Exeter, University of Nottingham, and the AERE 2024 Summer Conference. All errors and omissions remain our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Temperature and Maltreatment of Young Children
Mary F. Evans, Ludovica Gazze, and Jessamyn Schaller
NBER Working Paper No. 31522
August 2023, Revised October 2024
JEL No. I31, J12, J13, Q54

ABSTRACT

We estimate the impacts of temperature on alleged and substantiated child maltreatment among young children using administrative data from state child protective services agencies. Leveraging short-term weather variation, we find increases in the number of young children involved in cases of alleged and substantiated maltreatment during hot periods. Additional analysis identifies neglect as the temperature-sensitive maltreatment type, and we find some evidence that adaptation via air conditioning mitigates this relationship. Given that climate change will increase exposure to extreme temperatures, our findings speak to additional costs of climate change among the most vulnerable.

Mary F. Evans
LBJ School of Public Affairs
The University of Texas at Austin
PO Box Y
Austin, TX 78713
United States
mary.evans@austin.utexas.edu

Jessamyn Schaller
Robert Day School of Economics and Finance
Claremont McKenna College
500 E Ninth St
Claremont, CA 91711
and NBER
jschaller@cmc.edu

Ludovica Gazze
Department of Economics
University of Warwick
United Kingdom
Ludovica.Gazze@warwick.ac.uk

A data appendix is available at http://www.nber.org/data-appendix/w31522

1 Introduction

Child maltreatment in the United States is common and costly; almost 40% of children in a 2011 survey reported experiencing maltreatment by adulthood (Finkelhor et al., 2013). Victims of child maltreatment face lower educational achievement, poorer employment prospects, reduced earnings, and higher risks of substance abuse, mental health issues, criminal activity, and incarceration (Currie and Tekin, 2012; Currie and Spatz Widom, 2010; Cicchetti and Handley, 2019; Lansford et al., 2002; Mersky and Topitzes, 2010; Widom, 1989; Zielinski, 2009). Researcxh across disciplines has identified a range of household-level factors contributing to child maltreatment including poverty, family structure, mental health disorders, and substance abuse (Mulder et al., 2018). A few studies explore the impacts of broader environmental factors, such as natural disasters and extreme temperatures, on child abuse and neglect in localized case studies (Curtis et al., 2000; Keenan et al., 2004; Gruenberg et al., 2019; Mehta et al., 2022).

In this paper, we explore the contemporaneous relationship between temperatures and the maltreatment of young children using US county-level administrative child welfare data. Our analysis is motivated by a growing literature identifying channels through which extreme temperatures, and heat in particular, might affect observed child maltreatment outcomes. First, heat makes adults more aggressive and children more restless (Hsiang et al., 2013; Ranson, 2014; Heilmann et al., 2021; McCormack, 2023). Second, heat reduces cognitive function, increases impatience, and adversely impacts mental health (Taylor et al., 2016; Graff Zivin et al., 2018; Park et al., 2020; Mullins and White, 2019; Escobar Carias et al., 2024), which may affect parental decision-making. Third, extreme temperatures alter time use (Graff Zivin and Neidell, 2014; Cosaert et al., 2023a,b; Cohen and Gonzalez, 2024), which could lead to changes in parental supervision or the likelihood that maltreatment is witnessed and reported. Finally, hot temperatures foster environments in which children are at increased risk of harm. For example, open windows present a fall risk (Harris et al., 2011), heat increases danger for children left unattended in vehicles (Levenson, 2023), and swimming pools and other bodies of water present a higher risk to children at warm temperatures (Chauvin et al., 2020).

Our research is the first systematic analysis of the relationship between temperature and child maltreatment in the United States. We use an administrative census of reports to state child protective services (CPS) agencies to create county-level measures of alleged and substantiated maltreatment of young children by semimonthly period from 2006 to 2016 for hundreds of US counties. We link those measures to modeled daily weather data, counting the number of days in each period on which the maximum temperature falls within each of nine bins. Our empirical strategy exploits variation within counties across years in semimonthly period temperatures, allowing us to control for fixed and seasonal county-level factors. State-year fixed effects absorb policy variation and other changes across states over time and period fixed effects control for national idiosyncratic shocks.

We find that temperatures higher than 20° Celsius lead to increases in alleged and substantiated maltreatment of young children. In particular, an additional day of extreme heat (>35° Celsius) increases substantiated maltreatment by 0.5% relative to a day with maximum temperature 15-20° Celsius. Stratifying by maltreatment type, we find that victimization due to neglect, not physical abuse, is the category most sensitive to temperature—more young children are left at risk of serious harm on hot days. This underscores the potential importance of changes in time use, parental decision-making, and environmental risk as mechanisms. Results for cold temperatures show reductions in substantiated maltreatment on colder days, with likely reductions in reporting as well.

Our work makes key contributions to the existing bodies of research on child maltreatment and climate change. First, we identify extreme temperature as a contemporaneous risk factor for child maltreatment, and for child neglect in particular. This is important, as the cross-disciplinary literature on child maltreatment has primarily focused on household-level risk factors. Our paper additionally contributes to a growing literature on the determinants of child maltreatment that emphasizes causal identification using area studies, policy variation, and other natural experiments (e.g., Lindo et al. 2018, Evans et al. 2022, Rittenhouse 2023, Bullinger et al. 2023). Notably, our results for child neglect across the temperature spectrum are consistent with the recent findings of Gould et al. (2024), who document similar patterns in emergency department (ED) admissions related to accidental injuries and poisonings and find that young children in general have the strongest temperature gradient in ED admissions.

Our paper is also among a small number that speak to the potential impacts of climate change on children. Existing studies in economics focus on how temperature affects educational outcomes among older children (e.g., Park et al. 2020). Aside from birth outcomes (Barreca and Schaller, 2020), we know less about how temperature affects younger children, whose early life experiences may have longer-lasting impacts. Our findings present a novel channel through which climate change will adversely impact child welfare over the long run. Combining predictions from 15 global climate models in a back-of-the-envelope calculation, we estimate that over the period 2081-2100, climate change will lead to an average annual increase of 0.21 children aged 0-4 in 1,000 with a substantiated maltreatment case per county, an increase of 1.53% over the 2016 US mean. Additional findings suggest potential avenues for preventative intervention, including increasing air conditioning penetration in poor and rural areas and ensuring safe environments for children on hot days.

2 Background

Child maltreatment refers to abuse and neglect of children under age 18 by an adult in a custodial role. Most states recognize at least four types of child maltreatment: physical abuse, sexual abuse, emotional maltreatment, and neglect, with specific definitions varying across states. About 40% of child maltreatment victims are under age five (Children's Bureau, 2021). Most victims of child maltreatment, about 70% in 2019, are first-time victims (Children's Bureau, 2021).

Neglect is the most complex and most common type of child maltreatment, accounting for around three-fourths of substantiated cases in the US (Children's Bureau, 2021). Broadly, neglect occurs when the omission of care by a parent or caregiver places a child at risk of serious harm. Neglect can be acute or chronic in nature. Acute neglect can involve a single incident, such as failing to prevent a young child from wandering near a busy street or accessing drugs or poisonous substances. Chronic neglect occurs when a caregiver repeatedly fails to meet a child's basic physical, developmental, and/or emotional needs (Children's Bureau, 2019a).

All states have mandatory reporting laws related to child maltreatment; as of 2019, 47 states have laws that identify specific professionals as mandatory reporters (Children's Bureau, 2019b). Most frequently these include social workers, healthcare professionals, law enforcement officers, and educational and childcare personnel. CPS referrals can also come from non-professional sources such as neighbors or family members.[1] Once received, CPS evaluates whether a referral meets the criteria for investigation or for alternative response (e.g., provision of services). If so, then the referral is "screened in" and is considered a report.[2] After investigation by CPS, a report receives a disposition. If the alleged maltreatment is substantiated or indicated under state law, then the child is considered a victim of child maltreatment.

Given the extent of underreporting and the failure to substantiate valid allegations (Waldfogel, 1998), maltreatment measures based on administrative data, like those we construct, likely underestimate the true amount of child maltreatment. Moreover, interpreting maltreatment outcomes constructed from administrative data as reflecting the true, unobserved level of child maltreatment is complicated when the channels through which the data are generated are also potentially impacted.[3] Relevant to our setting, extremely cold weather

---

[1] In 2019, almost 70% of reports were submitted by professional sources (Children's Bureau, 2021).

[2] In 2019, about 54% of CPS referrals were screened in.

[3] This caveat also applies to maltreatment measures based on ED visits. See for example

generates unusual disruptions to the typical reporting channels, for example through transportation barriers and closures of school, childcare, and work facilities. It may also be more difficult for CPS to substantiate allegations if transportation barriers impact case workers' ability to investigate. Because we cannot differentiate changes in underlying maltreatment from reductions in reporting related to winter weather, we are cautious in our interpretation of results for cold temperatures.

3 Data

We form child maltreatment measures using the National Child Abuse and Neglect Data System (NCANDS) Child Files, which provide administrative data from referrals (i.e., reports) of child maltreatment to CPS agencies and the outcomes of subsequent investigations. These data were obtained through a restricted data agreement with NDACAN.[4] Each NCANDS Child File represents a census of screened-in CPS referrals that received a disposition in the respective federal fiscal year. We use the NCANDS Child Files for fiscal years 2006-2018, which cover almost all child maltreatment referrals received between 2006 and 2016.

Two features of the NCANDS data inform our research design. First, the most granular

Chaiyachati et al. (2022).

[4]The files were provided by the National Data Archive on Child Abuse and Neglect, and have been used with that permission. See Appendix A for the specific files we use. The data were originally collected under the auspices of the Children's Bureau. Funding was provided by the Children's Bureau, Administration on Children, Youth and Families, Administration for Children and Families, US Department of Health and Human Services. The collector of the original data, the funding agency, NDACAN, Cornell University, and the agents or employees of these institutions bear no responsibility for the analyses and interpretations presented here. The information and opinions expressed in this paper reflect solely the opinions of the authors.

geographic identifier available in the data is county, which is available only for cases from counties with at least 1,000 total cases in the fiscal disposition year. County is also masked in the event of a child's death. Second, we observe the semimonthly period, between the 1st and 15th days of the month or between the 16th and the end of month, during which the report of child maltreatment was made. The exact report and incident dates are masked.[5] Henceforth we refer to the "semimonthly period" as "period." Given these features of the data, we form a balanced county-by-period panel representing 433 counties in 42 states in the contiguous US for which we have daily weather data. Appendix A provides more details on construction of the panel. While the sample counties represent only 14% of US counties, collectively they account for almost two thirds of the US child population ages zero to four.

We form two primary maltreatment outcomes, the allegation rate and the victimization rate, both measured at the county-by-period level. The allegation rate is the number of children ages 0 to 4 per 1,000 with at least one screened-in maltreatment report in the county-period. The victimization rate reflects the number of children ages 0 to 4 per 1,000 considered to be victims of maltreatment in the county-period. A child is a victim if a maltreatment allegation is determined by investigation to be substantiated or indicated according to the definition under state law. While neither outcome is a perfect measure of the unobserved true level of maltreatment, the victimization rate is less likely to be sensitive to changes in reporting behavior than the allegation rate given the process for and challenges of substantiating allegations (Waldfogel, 1998). CPS workers face a burden of proof in substantiating cases and Cross and Casanueva (2009) find that children are more likely to be found victims when caseworkers perceive higher levels of harm and severity of the risk to the child. As a result, in discussing our findings, we focus primarily on the victimization rate

[5]Using a restricted version of the NCANDS no longer available to researchers, Benson et al. (2022) observed exact incident and report dates for some cases. For about 92% of these cases, incident and report dates were the same and for another 6%, the dates were within one week of each other.

outcome.

Annual child population data by county is from the Surveillance, Epidemiology, and End Results (SEER) Program. Figures A1, A2, and A3 show spatial and temporal variation in the allegation and victimization rates. We use additional information available in NCANDS to further refine the child maltreatment measures. Table A1 presents summary statistics for all maltreatment measures.

To measure temperature variation, we use the AN81d modeled daily weather data from the PRISM Climate Group at Oregon State University (PRISM Climate Group, Oregon State University, 2014). The 4x4 kilometer grid-level data on temperature and precipitation, available for the contiguous US, are interpolated from more than 10,000 weather stations based on monitored measures of temperature and precipitation using a model that accounts for factors that influence local climate (e.g., elevation, wind direction). For each weather variable and county, we compute the population-weighted spatial daily average of all grid cells that cover the county area.[6] Our results are robust to alternative construction and assignment of weather variables, as discussed in the next section. Following related work (e.g., Park et al. 2020, Barreca and Schaller 2020), we focus on daily maximum temperatures (Figure A4). For each county, we count the number of days in the reporting period in which the daily maximum temperature falls below 0 degrees Celsius, within each of 5-degree Celsius bins up to 35, or above 35 degrees Celsius. We also measure the average daily precipitation in decimeters over the reporting period by county.

Finally, we extract data from SEER, the Small Area Income and Poverty Estimates (SAIPE) program at the Census Bureau, and the Bureau of Labor Statistics. We create annual county-level control variables measuring race and ethnicity (e.g., share Black, share Hispanic) and economic conditions (e.g., share of children in poverty, median household income). Appendix Table A2 provides summary statistics for control variables.

---

[6]We construct population weights using gridded US Census data accessed on 12/19/2023 (Seirup and Yetman, 2006).

4 Empirical model and results

Consistent with other studies that measure the impacts of temperature exposure (e.g., Graff Zivin et al. 2018), we estimate high dimensional fixed effects models, as in the following specification:

$$
\begin{aligned}
Y_{it} = & \sum_j \beta^j (\text{N Days with MaxTemp}_{\text{it}} \text{ in Bin}_j) \\
& + \sum_j \sum_{l \in \{1,2\}} \gamma_l^j (\text{N Days with MaxTemp}_{\text{it}} \text{ in Lagged/Lead Period l in Bin}_j) \\
& + \pi X_{it} + \alpha Z_{iy(t)} + \eta_{iw(t)} + \phi_{s(i)y(t)} + \delta_t + \varepsilon_{it}
\end{aligned}
$$

where Y_{it} denotes the child maltreatment outcome in county i and period t. The variable $\text{N Days with MaxTemp}_{\text{it}} \text{ in Bin}_j$ counts the number of days in county i during period t in which the daily maximum temperature lies within 5-degree Celsius bin j. The model also includes two period lags and leads of the temperature variables, to allow for delayed effects and to check for spurious correlations, respectively. X_{it} denotes average daily precipitation in county i and period t as well as two period leads and lags of precipitation. $Z_{iy(t)}$ denotes a set of county-by-year controls. We include county-by-period fixed effects, $\eta_{iw(t)}$, to control for county-specific seasonality; state-by-year fixed effects, $\phi_{s(i)y(t)}$, to control for changes to state-specific policies over time as well as state economic trends; and reporting period fixed effects, δ_t, to control for idiosyncratic national shocks that may explain variation in allegation and victimization rates.[7] We cluster standard errors at the county level.

Figure 1 plots the estimated coefficients and 95% confidence intervals on three sets of temperature variables: (1) those associated with contemporaneous exposure (i.e., our pri-

[7]County-by-period fixed effects are defined based on the "calendar" semimonthly period (e.g., Los Angeles county for the first half of August).

mary coefficients of interest), indicated by circles; (2) those associated with lagged exposure, represented as diamonds; (3) those associated with future exposure, denoted with triangles. Panel 1a shows results for the allegation rate while panel 1b depicts results for the victimization rate. The excluded temperature bin is 15-20°C (59-68°F). Compared to moderate temperatures, we find that contemporaneous exposure to cold and hot temperatures is associated with changes in both maltreatment measures. Allegation and victimization rates are especially high above about 25°C and especially low in the lowest two temperature bins, with a weaker, roughly-linear relationship in between. We explore this pattern in more detail in the next section. Most of the estimated coefficients on leads and lags of temperature are not statistically different from zero.[8]

We zero in on the estimated coefficients for the highest temperature bin, above 35°, in Table 1 to summarize robustness of our results. The contemporaneous coefficients for this bin (i.e., the rightmost circles in panels (a) and (b) of Figure 1) are presented in Column 1. Standard errors clustered at the county level are reported in parentheses; standard errors clustered at the state level are reported in brackets. For the allegation rate in Panel A, the estimated coefficient represents the average increase in children age 0 to 4 with allegation(s) per 1,000 in the county-period associated with shifting the daily maximum temperature on one day in the reporting period from the reference temperature bin (15-20°C) to the highest temperature bin (above 35°C). Evaluated at the mean allegation rate of 3.459 children per 1,000, this represents a 0.7% increase. For the victimization rate in Panel B, the estimated coefficient is associated with a 0.54% increase when evaluated at the mean of 0.792 children per 1,000. If all counties in our sample experienced a one-day shift in maximum temperature

[8]Table A2 reports estimated coefficients and standard errors for control variables, including precipitation. A one standard deviation increases in contemporaneous precipitation is associated with around 0.01 standard deviation increases in allegation and victimization rates. We find no relationship between immediate past and future precipitation and the two child maltreatment outcomes.

from the 15-20°C range to above 35°C in one period, then this would translate into about ten more kids age 0 to 4 per 1,000 with maltreatment allegation(s) and almost two more victims per 1,000 among sample counties in that single period.

For context, we can compare the magnitude of the effects of hot temperatures with effects of policies aimed, directly or indirectly, at improving children's welfare. First, Sandner et al. (2022) estimate that a one-percentage point increase in childcare coverage in a German county reduces child maltreatment by 1%. Second, Rittenhouse (2023) and Bullinger et al. (2023) find that a $1,000 transfer decreases the probability that a child is referred to CPS by age two by 1.6% in California, and by age three by 10% in Alaska, respectively. These findings suggest that alleviating the time and budget constraints families face can reduce child maltreatment. The temperature effects we estimate are more modest. Nonetheless, they additionally suggest that transitory environmental shocks contribute to child maltreatment and that climate mitigation and attention to the relationship between environment and parental decision-making may also be important for child welfare.

The remaining columns of Table 1 explore robustness of the results for hot temperatures. Columns (2) through (5) consider different sets of fixed effects, column (6) removes temperature leads and lags, and column (7) includes county population weights. Estimated coefficients are stable across these alternative specifications. We additionally conduct several exercises to explore the sensitivity of our results to how we measure temperature. We find similar results when we define coarser and finer temperature bins (Figure A5) or construct weather variables using the area-weighted spatial average (Figure A6).

4.1 Evidence on mechanisms

In this section, we conduct additional analyses to shed light on the mechanisms through which temperatures affect maltreatment of young children. First, we draw on additional information about children and cases contained in NCANDS to identify how reporting changes with temperature, the types of maltreatment that respond to temperatures, and the children most affected. Second, we look at variation in the temperature-maltreatment relationship across counties with different characteristics. Third, we explore a different data source, time use surveys, to investigate how changes in caregivers' time use at different temperatures might relate to changes in child maltreatment.

4.1.1 From child and case characteristics

To assess the extent to which temperatures might affect reporting, we look at an alternative outcome, the substantiation rate. The substantiation rate is the fraction of children who are found to be victims of child maltreatment among those with allegations. If hot temperatures merely affect the reporting of child maltreatment but not the underlying level, then we would expect changes in the share of children found to be victims among those with allegations. For example, suppose children are more likely to play outside at hot temperatures compared to moderate temperatures and thus be more visible to neighbors or other potential reporters. If this merely increases the number of children with allegation(s) but leaves the number of victims unchanged, then the substantiation rate would be lower at hot temperatures. On the other hand, if more children are at risk and exposure to potential reporters increases at hot temperatures, then the impact on the substantiation rate is ambiguous.

Figure 1c depicts the estimated relationship between contemporaneous temperature and the substantiation rate. The estimated coefficients on hot temperatures are close to zero and statistically insignificant. Results for cold temperatures are noisier but suggest increases in contemporaneous substantiation rates in the lowest temperatures bins. This is consistent with likely obstruction of reporting for less severe cases in extreme cold weather, as discussed in Section 2. While such reductions in reporting are important in their own right and are potentially an area for future research—see, e.g. reductions in reporting during school breaks (Benson et al., 2022) and during the COVID-19 lockdown period (Baron et al., 2020; Shusterman et al., 2022)—they suggest a cautious approach to interpretation of the cold weather treatment effects that we observe.

Next, we seek to learn more about underlying mechanisms by distinguishing among different types of reporters. For example, suppose the reporting decisions of mandatory reporters, many of whom receive specific training on identifying likely child maltreatment, are less subject to biases that arise from the physiological impacts of heat exposure. If so, we would observe a different pattern of results, depending on the report source. We explore this by differentiating between professional and non-professional report sources.[9]

Figure A8 shows results, focusing on the estimated coefficients and 95% confidence intervals for contemporaneous temperatures. The left-hand panels report results for the allegation rate while the right-hand panels show results for the victimization rate. Across all four panels, we find increases at higher temperatures, with estimated coefficients that are relatively similar in magnitude beyond 25°C for each outcome. However, at cold temperatures, there are differences across reporting categories. For outcomes based on professional reports, there are both fewer children with allegations and fewer substantiated victims during the coldest periods (Panels A8a and A8b). For non-professional reporters, the allegation rate (Panel A8c) also falls at cold temperatures, but there is no corresponding statistically significant reduction in victimization rates (Panel A8d), suggesting that the reduction shown in Panel A8c likely reflects reduced reporting of cases that eventually would not have been substantiated.

We now explore which types of maltreatment are most affected by temperature. Because heat has documented effects on aggression and mood, as well as on cognitive function, hotter periods could be associated with increases in physical abuse and in neglect deriving from caregiver actions that might endanger the child. Additionally, if heat prompts other parental behaviors that put children at risk (e.g., domestic violence) then we may document a relationship between hot temperatures and emotional maltreatment.[10] The channel link-

[9] See the appendix for more details on the two categories.

[10] NCANDS recommends that states classify domestic violence as emotional maltreatment when submitting their data but compliance with this recommendation is unclear; the

ing exposure to extreme temperatures and sexual abuse is less clear. Figure 2 shows the estimated relationship between contemporaneous temperature and the victimization rate for these four types of child maltreatment. Notably, we find no consistent evidence that victimization rates for physical, sexual, or emotional abuse change with temperatures.[11] Rather, Figure 2b shows that the estimated effects of hot and cold temperatures on the victimization rate reported in Figure 1 are driven by changes in neglect, the most common maltreatment type. As acute neglect occurs when children are exposed to potentially harmful situations, this suggests that changes in parental time spent caring for children, attentiveness, and cognitive capacity might be key mechanisms. Unfortunately, we cannot distinguish among different types of neglect. Additionally, our data do not reflect the most severe instances of acute neglect in which a child dies.

To provide additional insight on the severity of risks to children at high temperatures, we use information in NCANDS on home removal and placement in foster care. For each county-period, we measure the number of children per 1000 removed from their homes within 60 days of the report period. We follow Baron et al. (2024) and restrict the sample to states and years in which foster care information is consistently reported, resulting in an unbalanced panel of 356 counties. Figure 1d shows results. While the estimated coefficients are noisy, the number of children whose cases result in removal weakly increases when temperatures are hot during the reporting period. The pattern of results for this alternative measure of child well-being reinforces our main results in Figure 1b.

Finally, we examine whether extreme temperatures affect maltreatment of children already engaged with CPS (intensive margin) or whether they bring new children into the CPS system (extensive margin). Proponents of abolishing the CPS system argue the costs to chil-

---

definition of emotional maltreatment varies under state law.

[11]Figure A9 shows results for the allegation rate. For physical abuse and emotional maltreatment, the estimated coefficients document reductions in the allegation rate at cold temperatures and increases at hot temperatures.

dren of CPS engagement are substantial, in particular for Black children (Roberts, 2022). If these costs outweigh benefits for some young children, then exploring the intensive and extensive margin responses is important for understanding the overall and distributional implications of extreme temperatures. To do so, we use additional information in the NCANDS on whether or not a child is known to be a victim of past maltreatment. Figure A10 shows that, compared to moderate temperatures, higher temperatures generally increase allegation and victimization rates for both prior victims and children without previous exposure to the child welfare system while cold temperatures primarily affect maltreatment outcomes for children with no prior exposure, who might have fewer encounters with mandatory reporters like social workers.

4.1.2 From county socioeconomic characteristics

Prior work on the relationship between exposure to hot temperatures and child outcomes (e.g., test scores, gestational length) has found moderating effects of air conditioning. To explore whether air conditioning has moderating effects in our setting, we use estimates of county-level air conditioning penetration in 2005 from Park et al. (2020).[12] Acknowledging that air conditioning is not randomly assigned, we also examine how our estimated temperature effects vary with median household income. Specifically, we construct interactions between our temperature bin variables and indicators for a county belonging to the low, medium, or top tercile of air conditioning crossed with having above- vs. below-median income in 2006.[13] We repeat this exercise for air conditioning and urbanicity using 2010 Census data on the percentage of the total population of the county represented by the urban population.

Figure 3 reports the estimated coefficients and 95% confidence intervals for the con-

[12] We thank Jisung Park for sharing these estimates.

[13] In our sample, the bottom tercile of counties has air conditioning penetration at or below 74%, while the top tercile has 100% penetration rate.

temporaneous temperature variables allowing for the relationship between contemporaneous temperature and child maltreatment to vary based on air conditioning penetration and income (Panel (a)), as well as air conditioning and urbanicity (Panel (b)).[14] We find some evidence that the effects of hot temperatures are driven by low-income and less urban counties with low rates of air conditioning.[15]

To explore whether habituation to warmer temperatures alters the temperature-maltreatment relationship, we re-estimate our main model by 2003 International Energy Conservation Code (IECC) climate zones .[16] Figure A7 reports our results for the victimization rate. Across climate zones, the pattern of estimated coefficients on warmer temperature bins is similar to our main results in Figure 1 although in some climate zones estimated coefficients are not statistically different from zero. That we fail to uncover a clear difference across climate zones may indicate that habituation does not substantially alter the relationship between hot temperatures and child maltreatment.

[14]Results for the allegation rate, presented in Figure A11, show similar patterns.

[15]For the hottest temperature bin, the low-income-low-air-conditioning group is statistically different at the 10% level from all other groups, except counties in the medium tercile of air conditioning and low income; the low-urbanicity-low-air-conditioning group is only statistically different, at the 5% level, from counties in the medium tercile of air conditioning and high income.

[16]We combine zones 1 (very hot humid/very hot dry) and 2 (hot humid/hot dry). We also combine zones 5 (cool humid/cool dry/cool marine), 6 (cold humid/cold dry), and 7 (very cold). Zones 3 (warm humid/warm dry/warm marine) and 4 (mixed humid/mixed dry/mixed marine) are treated as distinct categories. Data crosswalked to county was accessed at https://gist.github.com/philngo/d3e251040569dba67942 on March 8, 2024.

4.1.3 From time use data

Given our finding of increased child neglect during hot periods, it is possible that changes in parental time use, and in particular attentiveness to childcare are an important mechanism. To investigate the time use channel directly, we use data from the American Time Use Survey (ATUS).[17] As the ATUS time diaries are only available for adults, we are not able to directly examine the time use of children. Instead, we construct a sample of adults with children ages 0 to 5 in the household. Then, we create a set of time use variables that reflect minutes spent during a 24-hour reference period on work, housework, and sports and leisure, as well as active and secondary childcare. We define active childcare as time directly spent on "caring for and helping household children" and secondary childcare as time spent doing any other primary activity while having a child in care. We match the ATUS data to our temperature data by county and exact date of the reference period, and estimate regressions that include maximum temperature bins, precipitation, county-period fixed effects, state-year fixed effects, and day-of-week fixed effects. Results from this exercise are presented in Appendix Figure A12. Panel A12a does not show any statistically significant changes in parental time use spent in any of the three general categories (i.e., work, housework, sports and leisure) for either hot or cold temperatures. Panel A12b shows that there also are no significant changes in provision of secondary childcare but Panel A12b depicts significant decreases in time spent on *active* childcare in the warmest temperature bins.

5 Impact of Climate Change on Child Maltreatment

This section performs a back-of-the-envelope calculation to predict the change in child victimization in US counties due solely to changes in temperature under a plausible, non-worst case, climate change scenario.[18] We require two inputs. First, our results in Figure 1b show

[17]We obtained these data from IPUMS (Flood et al., 2024).

[18]We do not consider predicted changes in precipitation due to climate change.

the estimated effect of shifting the maximum temperature for one day in the county-period from the reference temperature bin to another 5°C bin on the number of children age 0 to 4 with a substantiated maltreatment case per 1,000. Second, we compute the predicted change in the number of days with maximum temperatures in each bin for each county-period in 2080-2100. Appendix Section A.2 provides details. Multiplying these two objects, we obtain estimates of the net effect of climate change on the US victimization rate under the assumptions that the temperature-maltreatment relationship will remain constant (e.g., no policy that could mitigate this relationship, such as increased AC, is adopted) and that the temperature-maltreatment relationship we estimate extends to all US counties.

Figure 4 plots the results of this exercise, extrapolating to 3,109 counties in the contiguous United States for which we have climate data.[19] It reports the estimated net annual change in the number of children aged 0-4 with a substantiated case of maltreatment per 1,000, averaged across counties, over 1,000 bootstrap replications for each of the 15 climate models we use. We estimate that over the period 2081-2100, climate change will lead to an average annual increase of 0.21 children aged 0-4 in 1,000 with a substantiated maltreatment case per county, an increase of 1.53% over the 2016 US-wide mean of 13.72 victims per 1000 children 0-4 (Children's Bureau, 2018).[20] 95% of our 15,000 estimates fall in the 0.008-0.397 range. An important caveat is that climate change might also affect other drivers of child maltreatment.

6 Conclusion

While a large literature identifies ongoing risk factors for child maltreatment, such as poverty and substance abuse, recent studies have emphasized the importance of shocks to family circumstances, including parental job loss (Lindo et al., 2018), income shocks (Rittenhouse,

[19]Estimates are similar when we focus on the set of sample counties (Figure A13a.)

[20]Effects are smaller when focusing on a closer period, 2040-2060 (Figure A13b).

2023), and natural disasters (Curtis et al., 2000). In this paper, we focus on effects that are even more acute—the effects of short-term variation in temperatures. We find robust evidence that hot temperatures increase maltreatment allegation and victimization rates for young children, with no evidence of differential substantiation during hotter periods.

Though our analysis is motivated in part by the established correlation between temperatures and adult aggression and violence, we do not find any evidence of increases in victimization rates for physical abuse or emotional maltreatment (which can proxy for domestic violence exposure) at hot temperatures. However, we caveat our findings noting that increased physical abuse of young children at home may be difficult to identify contemporaneously unless the abuse is severe enough to require medical care. Existing correlational evidence based on hospital data is mixed, with Gruenberg et al. (2019) finding an increases in abuse-related admissions on hot days, but Mehta et al. (2022) finding no increases in abusive head trauma.

Our results suggest instead that child neglect is measurably responsive to high temperatures—parents are intentionally or unintentionally allowing their young children to be in dangerous situations on hotter days. Examples of such behavior could include leaving young children in hot cars; unsupervised access to weapons or dangerous substances; or allowing children to play unattended in ways that could place them in danger (e.g., near a busy road or open window). Inattentive parenting could result from changes in time use or from reductions in adult cognitive capacity in hot weather (Almås et al., 2019). Additional research is warranted to study the relative contributions of these two factors, as well as the nature of the neglect incidents on hot days and the roles of specific risk factors in the home environment. Importantly, our data do not include fatal maltreatment cases, so our results do not speak to the relationship between temperatures and the most severe cases of child maltreatment.

Studying maltreatment of young children is notoriously difficult but crucially important. Because children who experience maltreatment are at increased risk of perpetrating child maltreatment as adults (Younas and Gutman, 2023), the adverse effects of increased child maltreatment are likely to persist across generations. In studies like ours that rely on administrative data, maltreatment outcomes reflect both reporting and the unobserved level of maltreatment. The coldest temperatures significantly obstruct some reporting pathways (e.g., due to transportation barriers, school and work closures). However, these pathways are largely still open at cool, moderate, and hot temperatures. We see additional exploration of the potentially differential impacts of shocks on underlying maltreatment and reporting as an important line of inquiry.

References

Almås, Ingvild, Maximilian Auffhammer, Tessa Bold, Ian Bolliger, Aluma Dembo, Solomon M Hsiang, Shuhei Kitamura, Edward Miguel, and Robert Pickmans, "Destructive behavior, judgment, and economic decision-making under thermal stress," Technical Report, National Bureau of Economic Research 2019.

Auffhammer, Maximilian, Solomon M Hsiang, Wolfram Schlenker, and Adam Sobel, "Using weather data and climate model output in economic analyses of climate change," *Review of Environmental Economics and Policy*, 2013.

Baron, E Jason, Ezra G Goldstein, and Cullen T Wallace, "Suffering in silence: How COVID-19 school closures inhibit the reporting of child maltreatment," *Journal of public economics*, 2020, *190*, 104258.

_ , Joseph J Doyle Jr, Natalia Emanuel, and Peter Hull, "Unwarranted Racial Disparity in US Foster Care Placement," Technical Report 2024.

Barreca, Alan and Jessamyn Schaller, "The impact of high ambient temperatures on delivery timing and gestational lengths," *Nature Climate Change*, 2020, *10* (1), 77–82.

Benson, Cassandra, Maria D Fitzpatrick, and Samuel Bondurant, "Beyond reading, writing, and arithmetic: The role of teachers and schools in reporting child maltreatment," *Journal of Human Resources*, 2022, pp. 0319–10084R2.

Bullinger, Lindsey R, Analisa Packham, and Kerri M Raissian, "Effects of Universal and Unconditional Cash Transfers on Child Abuse and Neglect," *National Bureau of Economic Research, WP31733*, 2023.

Burke, Marshall, John Dykema, David B Lobell, Edward Miguel, and Shanker Satyanath, "Incorporating climate uncertainty into estimates of climate change impacts," *Review of Economics and Statistics*, 2015, *97* (2), 461–471.

Carias, Michelle Escobar, David W Johnston, Rachel Knott, and Rohan Sweeney, "Temperatureâs toll on decision-making," *The Economic Journal*, 2024, *134* (663), 2746–2771.

Chaiyachati, Barbara H, Joanne N Wood, Camille Carter, Daniel M Lindberg, Thomas H Chun, Lawrence J Cook, Elizabeth R Alpern, PECARN Registry Study Group, and PECARN Child Abuse Special Interest Group, "Emergency department child abuse evaluations during COVID-19: a multicenter study," *Pediatrics*, 2022, *150* (1), e2022056284.

Chauvin, Marine, Tom Kosatsky, Marianne Bilodeau-Bertrand, Philippe Gamache, Audrey Smargiassi, and Nathalie Auger, "Hot weather and risk of drowning in children: opportunity for prevention," *Preventive medicine*, 2020, *130*, 105885.

Children's Bureau, "Child Maltreatment 2016, https://www.acf.hhs.gov/sites/default/files/documents/c Accessed: March 8th, 2023," 2018.

_ , "Chronic Child Neglect, Accessed: March 19th, 2023," 2019.

_ , "Mandatory reporters of child abuse and neglect, https://www.childwelfare.gov/topics/systemwide/laws-policies/statutes/manda/. Accessed: March 8th, 2023," 2019.

_ , "Child Maltreatment 2019, https://www.acf.hhs.gov/cb/report/child-maltreatment-2019. Accessed: March 8th, 2023," 2021.

Cicchetti, Dante and Elizabeth D Handley, "Child maltreatment and the development of substance use and disorder," *Neurobiology of stress*, 2019, *10*, 100144.

Cohen, Francois and Fidel Gonzalez, "Understanding the Link between Temperature and Crime," *American Economic Journal: Economic Policy*, 2024.

Cosaert, Sam, Adrián Nieto, and Konstantinos Tatsiramos, "Temperature and Joint Time Use," *IZA Institute for Labor Economics, DP16175*, 2023.

— **, Adrián Nieto Castro, and Konstantinos Tatsiramos**, "Temperature and the Timing of Work," *IZA Institute for Labor Economics, DP16480*, 2023.

Cross, Theodore P and Cecilia Casanueva, "Caseworker judgments and substantiation," *Child Maltreatment*, 2009, *14* (1), 38–52.

Currie, Janet and Cathy Spatz Widom, "Long-term consequences of child abuse and neglect on adult economic well-being," *Child maltreatment*, 2010, *15* (2), 111–120.

— **and Erdal Tekin**, "Understanding the cycle childhood maltreatment and future crime," *Journal of Human Resources*, 2012, *47* (2), 509–549.

Curtis, Thom, Brent C Miller, and E Helen Berry, "Changes in reports and incidence of child abuse following natural disasters," *Child abuse & neglect*, 2000, *24* (9), 1151–1162.

Evans, Mary F, Matthew C Harris, and Lawrence M Kessler, "The hazards of unwinding the prescription opioid epidemic: Implications for child maltreatment," *American Economic Journal: Economic Policy*, 2022, *14* (4), 192–231.

Finkelhor, David, Heather A Turner, Anne Shattuck, and Sherry L Hamby, "Violence, crime, and abuse exposure in a national sample of children and youth: An update," *JAMA pediatrics*, 2013, *167* (7), 614–621.

Flood, Sarah M., Liana C. Sayer, Daniel Backman, and Annie Chen, "American Time Use Survey Data Extract Builder Version 3.2 [Dataset]," 2024.

Gould, Carlos F., Sam Heft-Neal, Alexandra K. Heaney, Eran Bendavid, Christopher W. Callahan, Matthew Kiang, Joshua S. Graff Zivin, and Marshall Burke, "Temperature Extremes Impact Mortality and Morbidity Differently," *National Bureau of Economic Research, WP32195*, 2024.

Gruenberg, Blake C, Ryan D Brown, Michael P Anderson, and Amanda L Bogie, "The link between temperature and child abuse," *Trauma and Emergency Care*, 2019, *4* (2), 1–5.

Harris, Vaughn A, Lynne M Rochette, and Gary A Smith, "Pediatric injuries attributable to falls from windows in the United States in 1990–2008," *Pediatrics*, 2011, *128* (3), 455–462.

Heilmann, Kilian, Matthew E Kahn, and Cheng Keat Tang, "The urban crime and heat gradient in high and low poverty areas," *Journal of Public Economics*, 2021, *197*, 104408.

Hsiang, Solomon M, Marshall Burke, and Edward Miguel, "Quantifying the influence of climate on human conflict," *Science*, 2013, *341* (6151), 1235367.

Keenan, Heather T, Stephen W Marshall, Mary Alice Nocera, and Desmond K Runyan, "Increased incidence of inflicted traumatic brain injury in children after a natural disaster," *American journal of preventive medicine*, 2004, *26* (3), 189–193.

Lansford, Jennifer E, Kenneth A Dodge, Gregory S Pettit, John E Bates, Joseph Crozier, and Julie Kaplow, "A 12-year prospective study of the long-term effects of early child physical maltreatment on psychological, behavioral, and academic problems in adolescence," *Archives of pediatrics & adolescent medicine*, 2002, *156* (8), 824–830.

Levenson, Michael, "Dozens of Children Die Every Year in Hot Cars. Could Technology Save Them?," *International New York Times*, 2023, pp. NA–NA.

Lindo, Jason M, Jessamyn Schaller, and Benjamin Hansen, "Caution! Men not at work: Gender-specific labor market conditions and child maltreatment," *Journal of Public Economics*, 2018, *163*, 77–98.

McCormack, Kristen, "Education Under Extremes: Temperature, Student Absenteeism, and Disciplinary Infractions," 2023.

Meehl, Gerald A, Curt Covey, Thomas Delworth, Mojib Latif, Bryant McAvaney, John FB Mitchell, Ronald J Stouffer, and Karl E Taylor, "The WCRP CMIP3 multimodel dataset: A new era in climate change research," *Bulletin of the American meteorological society*, 2007, *88* (9), 1383–1394.

Mehta, Nehali, Laura Bliss, Anne Trolard, and Jamie S Kondis, "The relationship between temperature and temporal patterns and incidence of abusive head trauma in a Midwest region hospital," *Child maltreatment*, 2022, *27* (2), 194–201.

Mersky, Joshua P and James Topitzes, "Comparing early adult outcomes of maltreated and non-maltreated children: A prospective longitudinal investigation," *Children and Youth Services Review*, 2010, *32* (8), 1086–1096.

Miller, Steve, Kenn Chua, Jay Coggins, and Hamid Mohtadi, "Heat waves, climate change, and economic output," *Journal of the European Economic Association*, 2021, *19* (5), 2658–2694.

Mulder, Tim M, Kimberly C Kuiper, Claudia E van der Put, Geert-Jan JM Stams, and Mark Assink, "Risk factors for child neglect: A meta-analytic review," *Child abuse & neglect*, 2018, *77*, 198–210.

Mullins, Jamie T and Corey White, "Temperature and mental health: Evidence from the spectrum of mental health outcomes," *Journal of health economics*, 2019, *68*, 102240.

Ortiz-Bobea, Ariel, "The empirical analysis of climate change impacts and adaptation in agriculture," in "Handbook of agricultural economics," Vol. 5, Elsevier, 2021, pp. 3981–4073.

Park, R Jisung, Joshua Goodman, Michael Hurwitz, and Jonathan Smith, "Heat and learning," *American Economic Journal: Economic Policy*, 2020, *12* (2), 306–39.

PRISM Climate Group, Oregon State University, "PRISM Gridded Climate Data, https://prism.oregonstate.edu. Accessed: March 8th, 2023," 2014.

Ranson, Matthew, "Crime, weather, and climate change," *Journal of environmental economics and management*, 2014, *67* (3), 274–302.

Riahi, Keywan, Detlef P Van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C O'neill, Shinichiro Fujimori, Nico Bauer, Katherine Calvin, Rob Dellink, Oliver Fricko et al., "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview," *Global environmental change*, 2017, *42*, 153–168.

Rittenhouse, Katherine, "Income and Child Maltreatment: Evidence from a Discontinuity in Tax Benefits," *Available at SSRN 4349231*, 2023.

Roberts, Dorothy, *Torn Apart: How the Child Welfare System Destroys Black Families–and How Abolition Can Build a Safer World*, Basic Books, 2022.

Sandner, Malte, Stephan L Thomsen, and Libertad González, "Preventing Child Maltreatment: Beneficial Side Effects of Public Childcare," 2022.

Seirup, Lynn and Greg Yetman, "US Census Grids (Summary File 1), 2000. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC)," 2006.

Shusterman, Gila R, John D Fluke, Juan J Nunez, Nicole B Fettig, and Bethel K Kebede, "Child maltreatment reporting during the initial weeks of COVID-19 in the US: Findings from NCANDS," *Child Abuse & Neglect*, 2022, *134*, 105929.

Taylor, Lee, Samuel L Watkins, Hannah Marshall, Ben J Dascombe, and Josh Foster, "The impact of different environmental conditions on cognitive function: a focused review," *Frontiers in physiology*, 2016, *6*, 372.

Waldfogel, Jane, *The future of child protection: How to break the cycle of abuse and neglect*, Harvard University Press Cambridge, MA, 1998.

Widom, Cathy Spatz, "The cycle of violence," *Science*, 1989, *244* (4901), 160–166.

Younas, Fatima and Leslie Morrison Gutman, "Parental risk and protective factors in child maltreatment: A systematic review of the evidence," *Trauma, Violence, & Abuse*, 2023, *24* (5), 3697–3714.

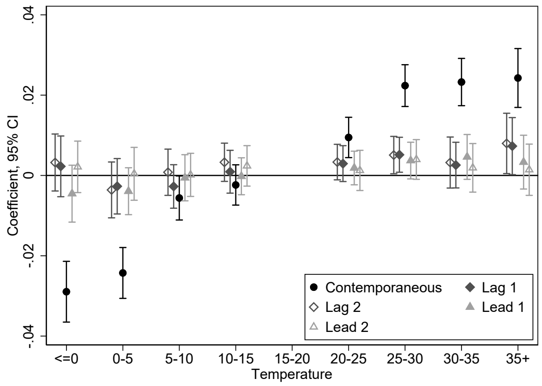
Zielinski, David S, "Child maltreatment and adult socioeconomic well-being," *Child abuse & neglect*, 2009, *33* (10), 666–678.

Zivin, Joshua Graff and Matthew Neidell, "Temperature and the allocation of time: Implications for climate change," *Journal of Labor Economics*, 2014, *32* (1), 1–26.

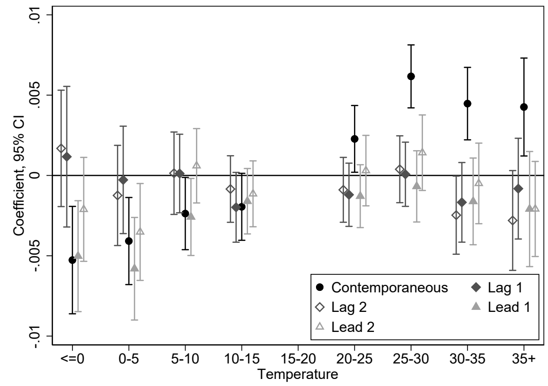
_ , Solomon M Hsiang, and Matthew Neidell, "Temperature and human capital in the short and long run," *Journal of the Association of Environmental and Resource Economists*, 2018, *5* (1), 77–105.

Figures and Tables

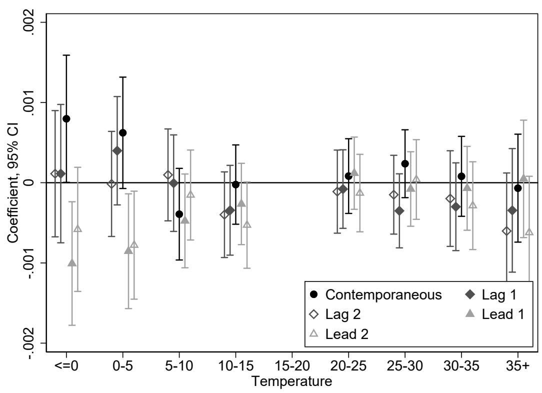
Figure 1: Relationship between Temperature and Maltreatment of Young Children



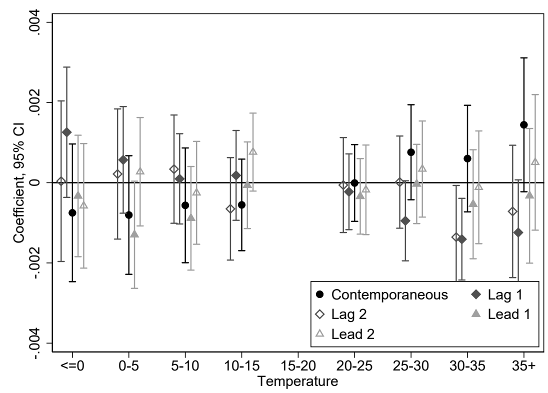
(a) Allegation rate



(b) Victimization rate



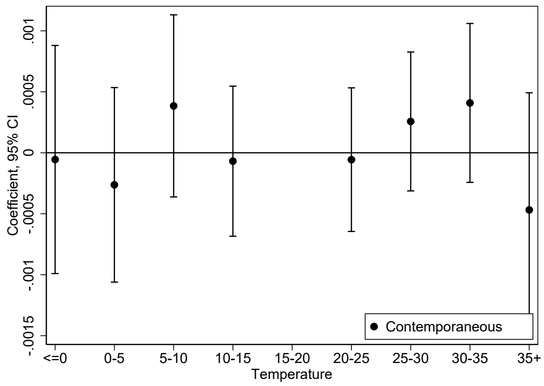
(c) Substantiation rate



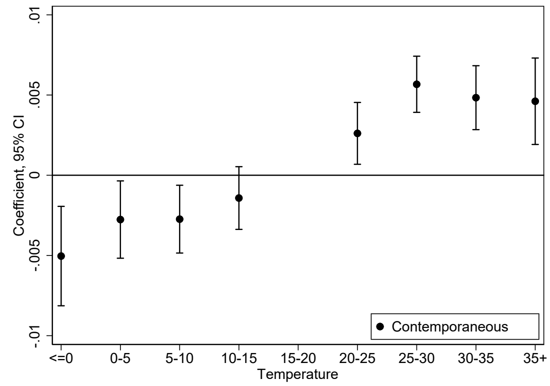
(d) Foster care removal rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the temperature bin variables in the main specification. The estimated coefficients of interest are in orange and denoted with circles. Diamonds denote estimated coefficients on lagged temperature variables while triangles indicate estimated coefficients on lead temperature variables. Panel (a) reports results for the allegation rate, the number of children per 1,000 with at least one maltreatment allegation in the county-period. The sample mean (standard deviation) allegation rate is 3.459 (2.100). Panel (b) plots results for the victimization rate, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation in the county-period. The sample mean (standard deviation) victimization rate is 0.792 (0.725). Panel (c) reports results for the substantiation rate, the fraction of children age 0-4 who are found to be victims of child maltreatment among those with allegation(s) in the county-period. Panel (d) plots results for the foster care removal rate, the number of children age 0-4 per 1,000 in the county-period who were removed and placed in foster care within 60 days. The sample mean (standard deviation) substantiation rate is 0.233 (0.143). The sample mean foster care removal rate is 0.194 (0.235).

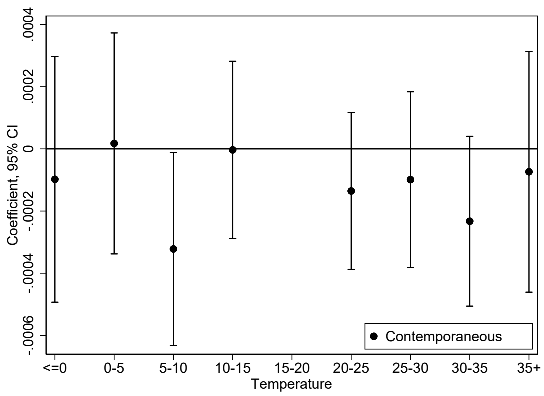
Figure 2: Relationship between Temperature and Victimization Rate of Young Children by Maltreatment Type



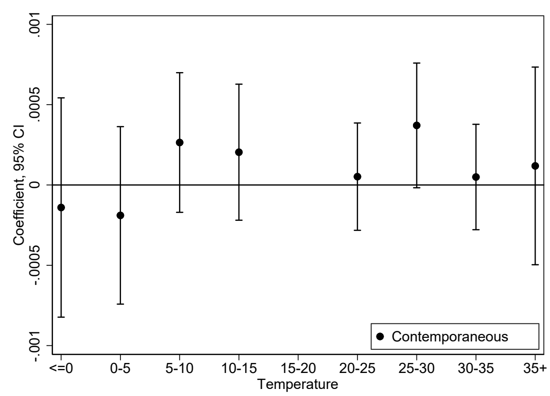
(a) Physical abuse



(b) Neglect



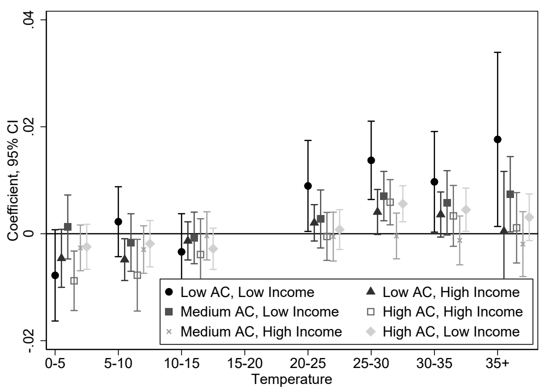
(c) Sexual abuse



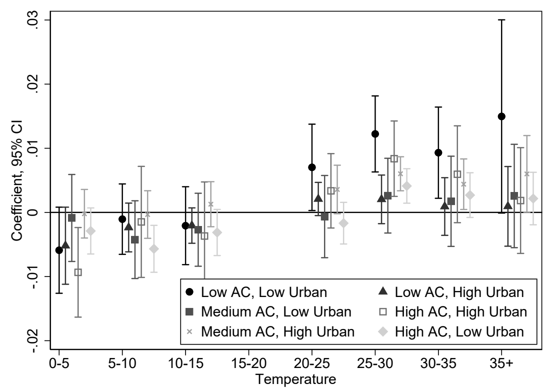
(d) Emotional maltreatment

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. For each panel, the results show the estimated relationship between temperature and the victimization rate where the rate is calculated by type of maltreatment. Panel (a) shows results for physical abuse; panel (b) shows results for neglect; panel (c) reports results for sexual abuse; panel (d) provides results for emotional or psychological maltreatment. The victimization rate is the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation of the respective type during the county-period.

Figure 3: Relationship between Temperature and Victimization Rate of Young Children by Air Conditioning Penetration, Median Household Income, and Urbanicity



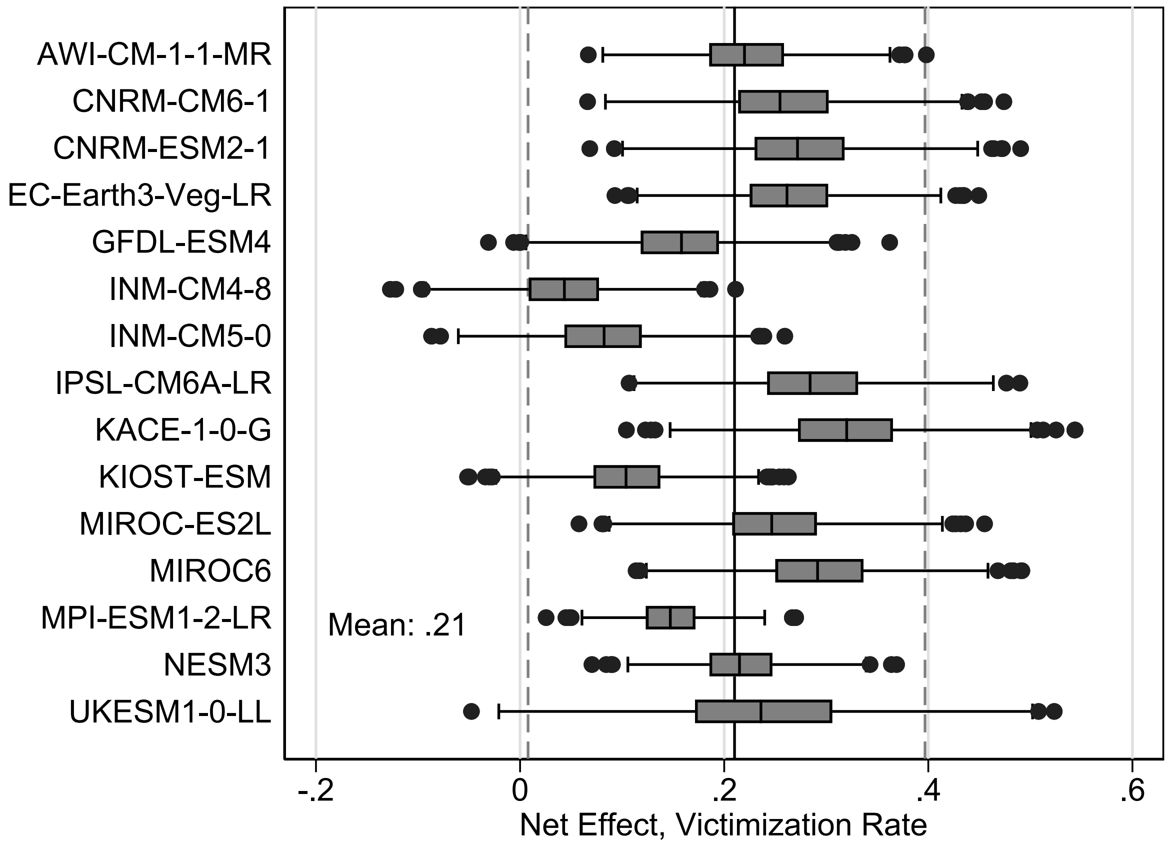
(a) Median household income



(b) Percent urban

Notes: This figure plots estimated coefficients and sums of estimated coefficients as appropriate, and 95% confidence intervals. Panel (a) reflects a specification that includes interactions among the contemporaneous temperature bin variables and six indicators for types of counties by median household income (above/below median) and residential air conditioning penetration rate in 2005 (by tercile). Panel (b) is constructed similarly but reflects a specification with interactions among the contemporaneous temperature bin variables and six indicators for types of counties by urbanicity (above/below median) and residential air conditioning penetration rate in 2005 (by tercile). Dots indicate low-AC and low-income/urbanicity counties, triangles low-AC and high-income/urbanicity counties, squares medium-AC and low-income/urbanicity counties, hollow squares medium-AC and high-income/urbanicity counties, Xs high-AC and low-income/urbanicity countiesm, and diamonds high-AC and high-income/urbanicity counties. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. This figure plots results for the victimization rate.

Figure 4: Average Predicted Change in Victimization Rate for Young Children in 2081-2100 Due to Climate Change, US-wide



Notes: This figure plots the estimated change in the victimization rate of children aged 0-4 attributable to climate change, that is the change in the average number of children per 1,000 with at least one substantiated maltreatment allegation. It reports results for 15 climate models across 1,000 bootstrap replications of our main specification. For each model, we report the minimum and maximum estimates obtained, alongside the median, as well as first, and third quartiles. The vertical dashed gray lines report the 2.5^{th} and 97.5^{th} percentiles across all models and bootstrap replications (0.008 and 0.397, respectively), while the vertical solid line reports the overall mean, 0.21.

Table 1: Relationship Between Temperature and Maltreatment of Young Children: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Allegation rate							
35+ Celsius	0.0243***	0.0208***	0.0180***	0.0179***	0.0224***	0.0244***	0.0174***
	(0.00374)	(0.00333)	(0.00291)	(0.00292)	(0.00347)	(0.00403)	(0.00248)
	[0.00688]	[0.00574]	[0.00425]	[0.00430]	[0.00598]	[0.00710]	[0.00353]
Panel B: Victimization rate							
35+ Celsius	0.00426**	0.00419**	0.00288*	0.00290*	0.00377*	0.00330*	0.00322***
	(0.00156)	(0.00146)	(0.00135)	(0.00136)	(0.00148)	(0.00158)	(0.000818)
	[0.00133]	[0.00128]	[0.00117]	[0.00115]	[0.00132]	[0.00143]	[0.000717]
County-year & precipitation controls	Yes	No	Yes	Yes	Yes	Yes	Yes
County-semimonthly period	Yes	No	No	No	No	Yes	Yes
County-month fixed effects	No	Yes	No	No	Yes	No	No
State-year fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Reporting period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	No	Yes	No	No	No	No	No
County fixed effects	No	No	Yes	Yes	No	No	No
County X linear year	No	No	No	Yes	No	No	No
Temperature lags	Yes	Yes	Yes	Yes	Yes	No	Yes
Temperature leads	Yes	Yes	Yes	Yes	Yes	No	Yes
County population weights	No	No	No	No	No	No	Yes

NOTES: Table reports the estimated coefficients on the highest temperature bin variable, 35+ degrees Celsius, based on the contemporaneous measure for the allegation rate (Panel A) and the victimization rate (Panel B). Column (1) reflects our baseline estimates. Columns (2) through (5) report results with varying sets of fixed effects. Column (6) uses the baseline set of fixed effects but removes temperature leads and lags. Column (7) weighs observations by county population age 0-4. Sample includes 114,312 observations, which represent 433 unique counties for 264 semimonthly periods. * statistically significant at the 10% level; ** statistically significant at the 5% level; *** statistically significant at the 1% level;

A Online Appendix

Temperature and Child Maltreatment by Mary F. Evans, Ludovica Gazze, and Jessamyn Schaller

A.1 Constructing Panel Dataset

In this Appendix we describe the process by which we form a balanced county-by-semimonthly period panel using the NCANDS Child Files for 2006 to 2018, specifically FFY2006v5, FFY2007v6, FFY2008v5, FFY2009v6, FFY2010v5, FFY2011v5, FFY2012v5, FFY2013v5, FFY2014v4, FFY2015v4, FFY2016v3, FFY2017v1, and FFY2018v2. The NCANDS Child File for a given year includes case-level data on all cases that received a disposition from a child protection services (CPS) agency in the federal fiscal year. A case represents a child-report pair. About 98 percent of cases receive a disposition within two years of being reported (e.g., a report submitted in 2006 is almost certain to appear in the 2006, 2007 or 2008 Child Files).

We first identify the 435 counties that are unmasked in all 13 Child Files from 2006 to 2018. We then remove observations from the counties that are not continuously unmasked in the Child Files between 2006 and 2018, those from Puerto Rico (due to data quality concerns), observations for which county of report is masked or missing including child fatalities, and observations with a report year earlier than 2006 or later than 2016. The next step involves identifying observations that appear in multiple Child Files. For these, we follow the recommendation in the NCANDS User's Guide to keep only the observations from the most recent fiscal year. The next step in constructing the panel involves appending together all of the relevant Child Files.

We construct maltreatment outcomes at the child-level. To do so we collapse the appended data to create a count of the number of unique children under age five with at least one allegation, with at least one substantiated allegation, etc. in the county-period. We then divide the resulting counts by the annual 0-4 child population in the county measured in thousands from SEER. The resulting balanced county-by-period panel represents 435 unique counties and 264 unique bimonthly reporting periods during the 11-year sample period.

Finally, we drop two counties that do not belong to the contiguous United States as we do not have weather data for them. Thus, we obtain a balanced panel of 433 counties in 42 states.

Less than 0.001% of child-level observations (prior to collapsing) have missing values for maltreatment type. These are excluded from the maltreatment-specific outcomes measures we construct. About 0.06% have missing values for report source. We assign the following report sources to the "professional reporter" category: social services personnel; medical personnel; mental health personnel; legal, law enforcement, and criminal justice personnel; education personnel; child daycare provider. The following report sources are categorized as "non-professional reporters": substitute care provider, alleged victim, parent, other relative, friends/neighbors, alleged perpetrator, anonymous reporter, other, unknown or missing. About 0.76% of the child-level observations have missing values for the prior victimization variable; children with missing values are not reflected in the child maltreatment measures we use for this component of our analysis.

The foster care removal rate reflects the number of children per 1000 in the county-period who were known to be removed from their homes and placed in foster care with 60 days of the period. For this outcome, we follow (Baron et al., 2024) and restrict attention to counties located in state-years during which foster care information is reported to NCANDS, yielding an unbalanced panel of 376 counties for the sample time period.

A.2 Computing Changes in Future Temperatures Due to Climate Change

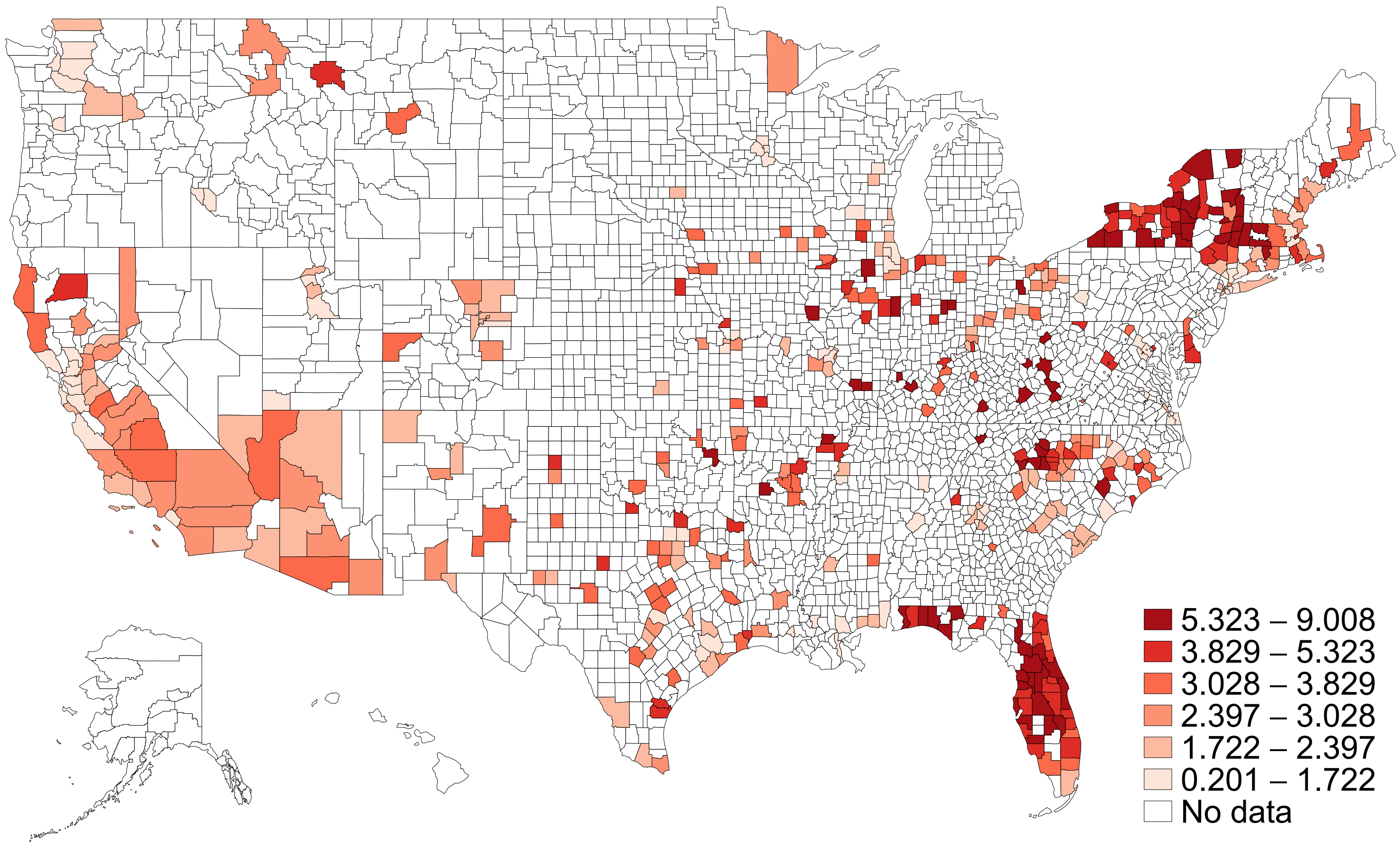
To predict $\Delta\mathbf{C}$, we leverage state-of-the-art techniques and climate change projections. We use daily climate estimates averaged over the period 2080-2100 from 15 global climate models included in Phase 6 of the Coupled Model Intercomparison Project, or CMIP (Meehl et al., 2007) which we assign to counties based on the population-weighted spatial average of cells covering each county.[21] To account for well-documented discrepancies between model predictions and measured and modelled current temperatures (Auffhammer et al., 2013; Ortiz-Bobea, 2021), we downscale these estimates using historical predictions for these models and historical PRISM temperature estimates for the period 1981-2000. We use these downscaled daily predictions to compute the predicted number of days in each temperature bin for the 24 semimonthly periods corresponding to our reporting periods in an average year in 2080-2100. Finally, we subtract the number of days in each temperature bin and reporting period averaged over our sample period to obtain our desired $\Delta\mathbf{C}$.

This exercise faces two dimensions of uncertainty. First, there is uncertainty in our estimates of the temperature-maltreatment relationship (regression uncertainty), which is usually represented by confidence intervals. Second, there is uncertainty in climate projections, represented by the 15 different climate models. To account for regression uncertainty, we follow Burke et al. (2015) and bootstrap our main specification sampling observations 1,000 times with replacement. We then multiply each of these 1,000 sets of estimated effects by the $\Delta\mathbf{C}$ obtained from each of the 15 climate models, to allow for uncertainty in the climate projections. Thus, this exercise yields a vector of 15,000 bootstrap replications for each county, which reflect both sources of uncertainty.

[21] We use estimates from the following models: AWI-CM-1-1-MR, CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3-Veg-LR, GFDL-ESM4, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, KACE-1-0-G, KIOST-ESM, MIROC-ES2L, MIROC6, MPI-ESM1-2-LR, NESM3, UKESM1-0-LL. We downloaded these estimates from the Copernicus's Climate Data Store using the function `download_cmip6_ecmwfr` in the R package `ecmwfr`. We selected the Shared Socioeconomic Pathway 245, a "middle of the road" socioeconomic scenario corresponding to Representative Concentration Pathway (RCP) such that radiative forcing reaches a level of 4.5 Watts/m2 in 2100 (Miller et al., 2021; Riahi et al., 2017).

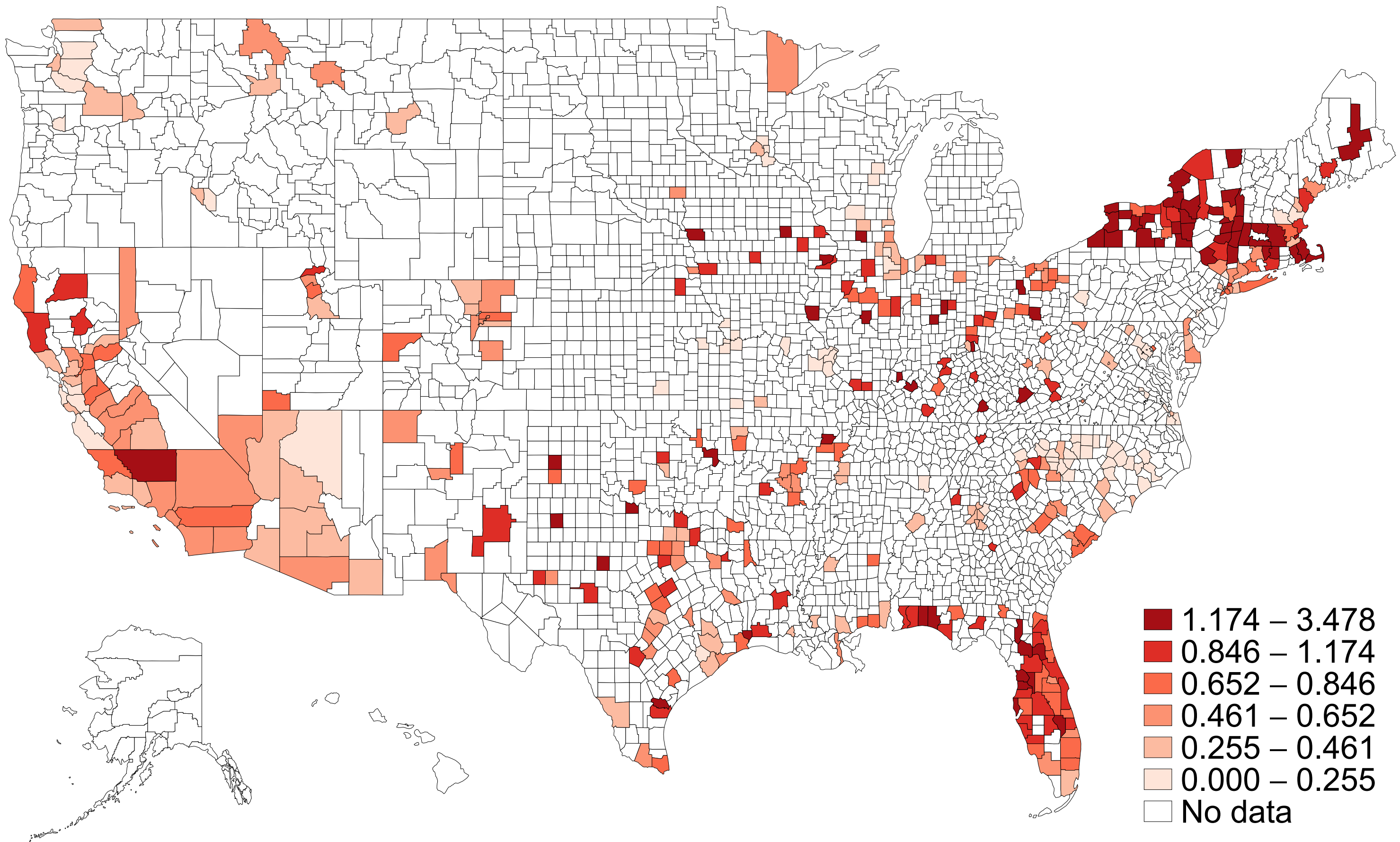
A.3 Additional figures and tables

Figure A1: Spatial Variation in Allegation Rates for Young Children



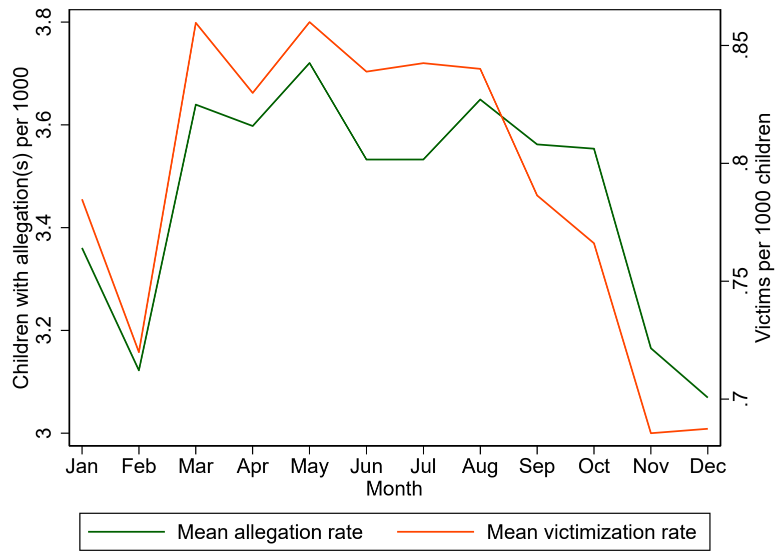
Notes: This figure plots the median allegation rate for each sample county during the sample period, 2006 to 2016. The allegation rate measures the number of children age 0-4 per 1,000 with at least one maltreatment allegation in the county-semimonthly reporting period.

Figure A2: Spatial Variation in Victimization Rates for Young Children

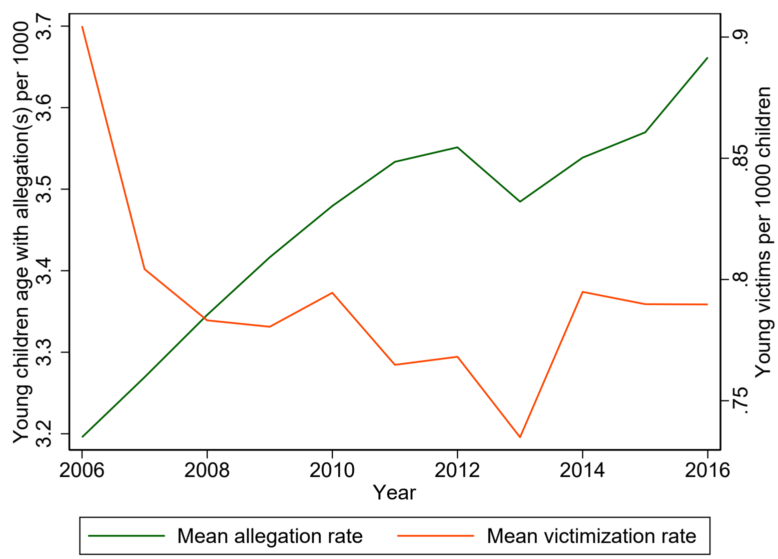


Notes: This figure plots the median victimization rate for each sample county during the sample period, 2006 to 2016. The victimization rate measures the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation in the county-semimonthly reporting period.

Figure A3: Monthly and Annual Variation in Child Maltreatment



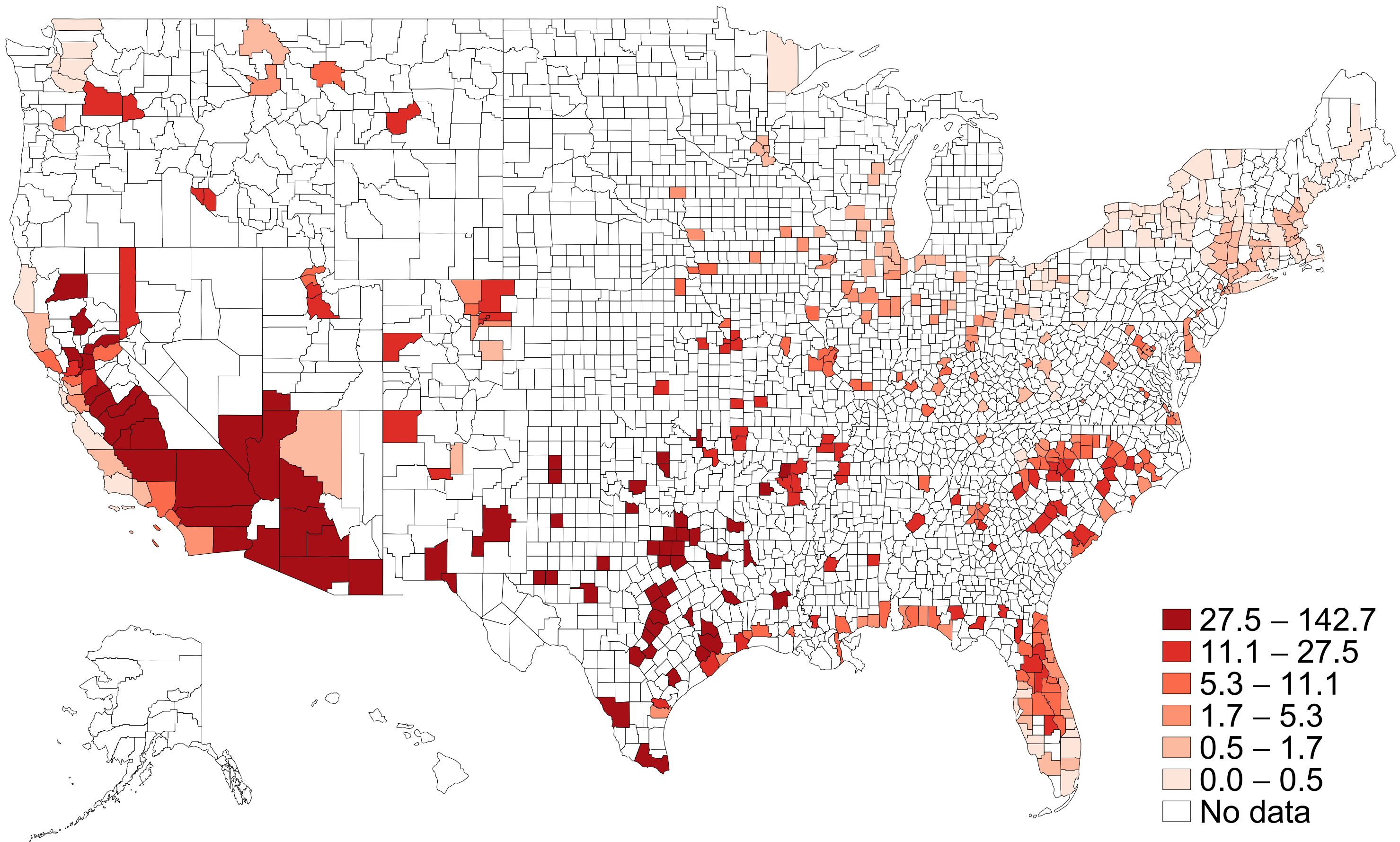
(a) Monthly mean allegation and victimization rates



(b) Annual mean allegation and victimization rates

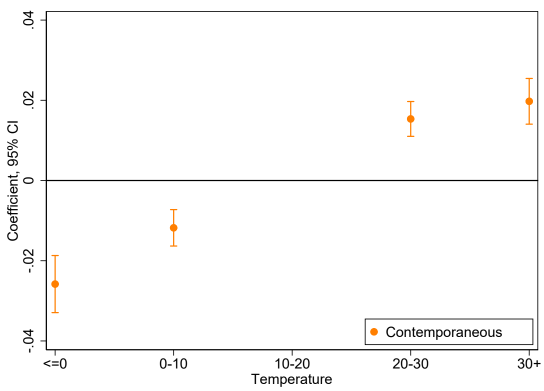
NOTES: Panel (a) of this figure plots the monthly means of allegation and victimization rates for children ages 0 to 4 during the sample period, 2006 to 2016. Panel (b) plots the annual means of the allegation (left y-axis) and victimization (right y-axis) rates for the sample period, 2006 to 2016. The allegation rate measures the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the semimonthly reporting period. The victimization rate measures the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the semimonthly reporting period.

Figure A4: Spatial Variation in Maximum Temperatures

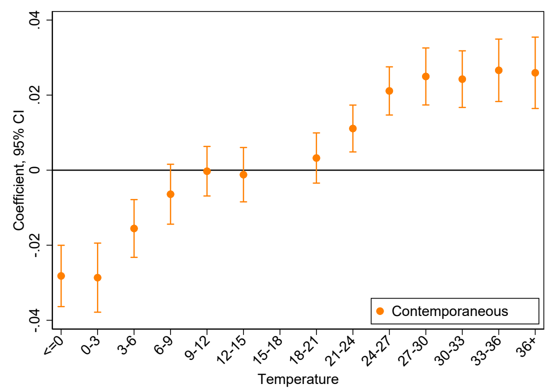


NOTES: This figure shows the average annual number of days in each county with maximum temperatures above 35 °C over the sample period, 2006-2016.

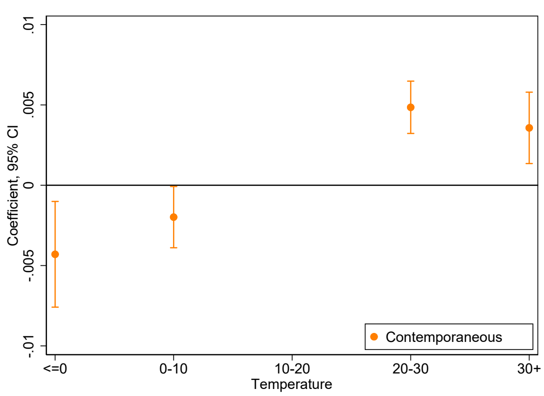
Figure A5: Relationship between Temperature and Maltreatment of Young Children, Alternative Temperature Bins



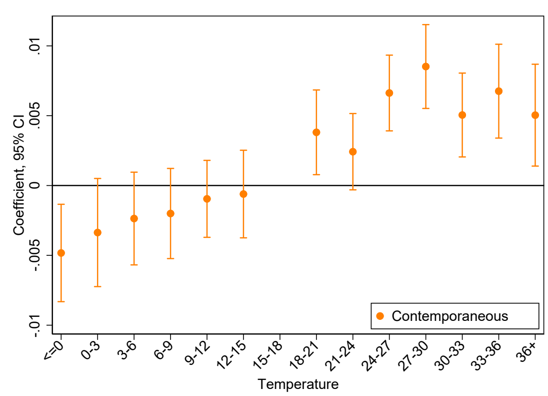
(a) Allegation rate: 10-degree bins



(b) Allegation rate: 3-degree bins



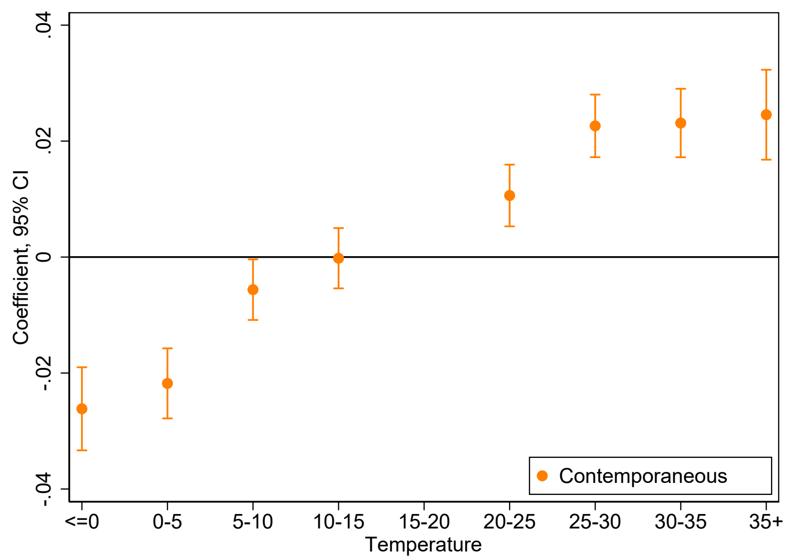
(c) Victimization rate: 10-degree bins



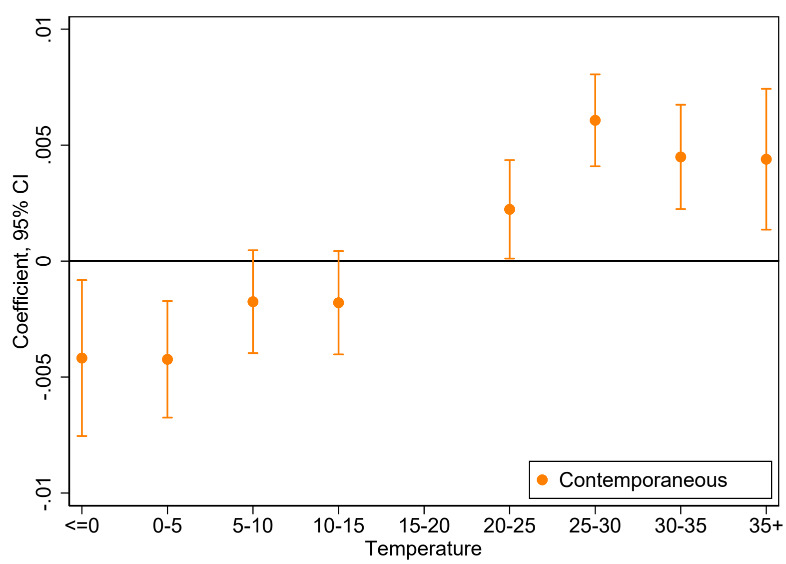
(d) Victimization rate: 3-degree bins

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables defined over 10°C intervals (Panels (a) and (c)) and over 3°C intervals (Panels (b) and (d)), respectively. Controls and fixed effects are as described in the main specification. Panels (a) and (b) report results for the allegation rate, the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the county-period. Panels (c) and (d) plot results for the victimization rate, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the county-period.

Figure A6: Relationship between Temperature and Maltreatment of Young Children, Alternative Assignment of Weather Variables



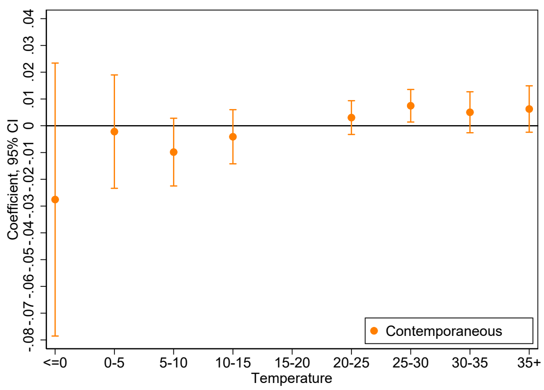
(a) Allegation rate



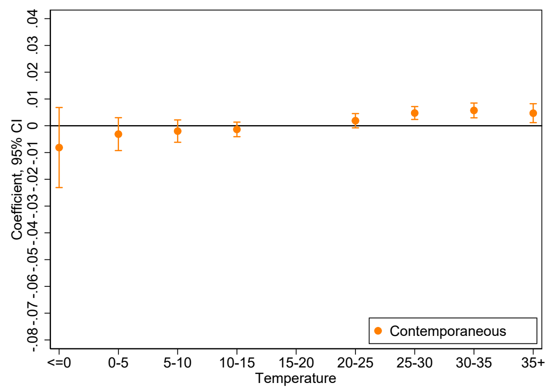
(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Panel (a) reports results for the allegation rate, the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the county-period. Panel (b) plots results for the victimization rate, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the county-period. Temperature and precipitation measures are assigned to each county by averaging across grid cells that intersect the county polygon and weighing observations by the fraction of county surface they cover.

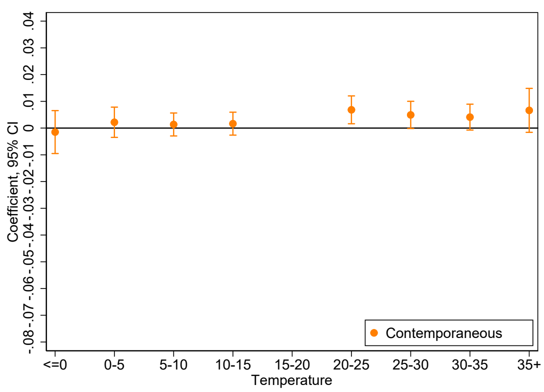
Figure A7: Relationship between Temperature and Victimization Rate for Young Children by Climate Zone



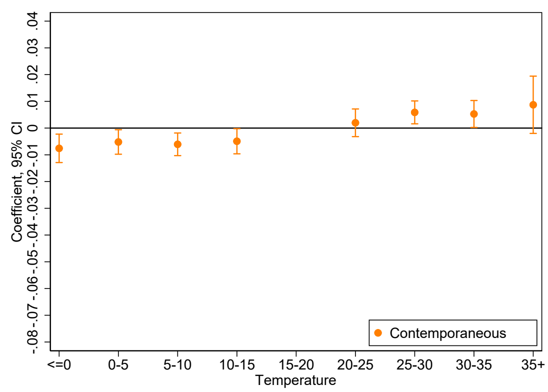
(a) Zones 1-2



(b) Zone 3



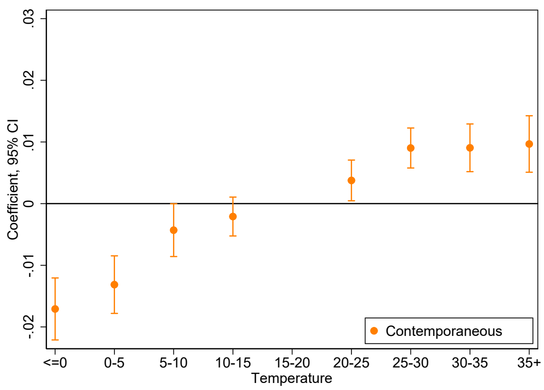
(c) Zone 4



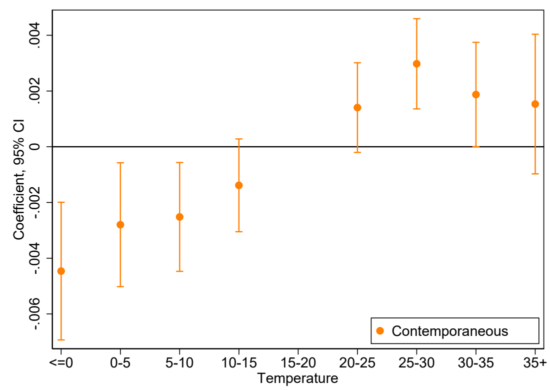
(d) Zones 5-7

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. For each panel, the results show the estimated relationship between temperature and the victimization rate for sub-samples based on climate zone using 2003 International Energy Conservation Code designations. Panel (a) through (d) report results for 80 counties in climate zones 1 and 2; 112 counties in zone 3; 88 counties in zone 4; and 135 counties in zones 5, 6 and 7, respectively. The victimization rate is the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the county-period.

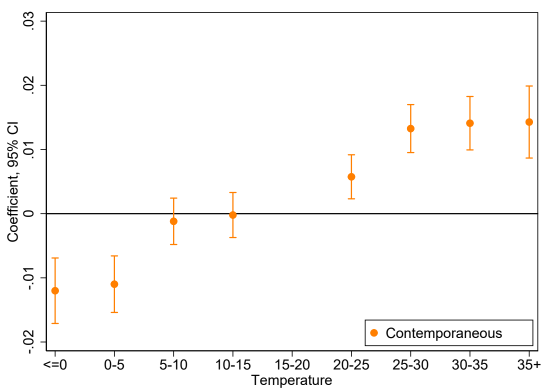
Figure A8: Relationship between Temperature and Maltreatment of Young Children by Report Source



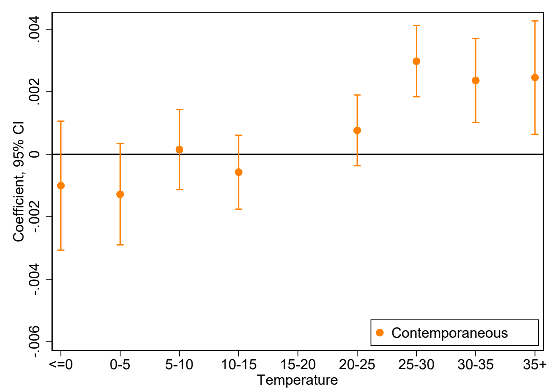
(a) Allegation rate, professional



(b) Victimization rate, professional



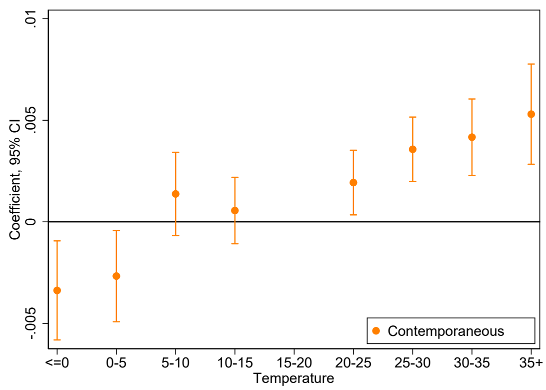
(c) Allegation rate, non-professional



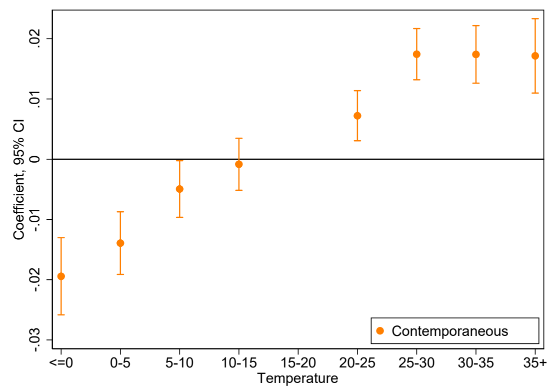
(d) Victimization rate, non-professional

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Panels (a) and (c) report results for the allegation rate, the number of children age 0-4 per 1,000 with at least one maltreatment allegation in the county-period. Panels (b) and (d) plot results for the victimization rate, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation in the county-period. Panels (a) and (b) show results based on reports from professional sources while (c) and (d) depict results based on reports for non-professional sources.

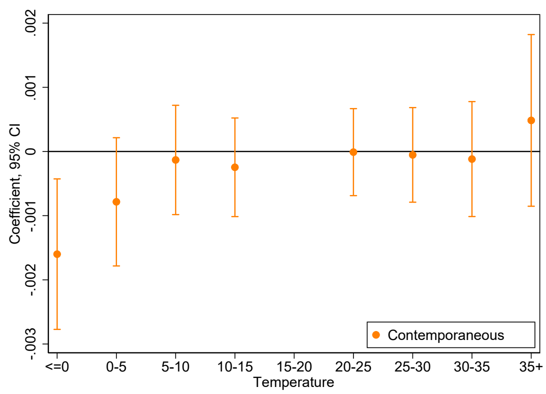
Figure A9: Relationship between Temperature and Allegation Rate for Young Children by Maltreatment Type



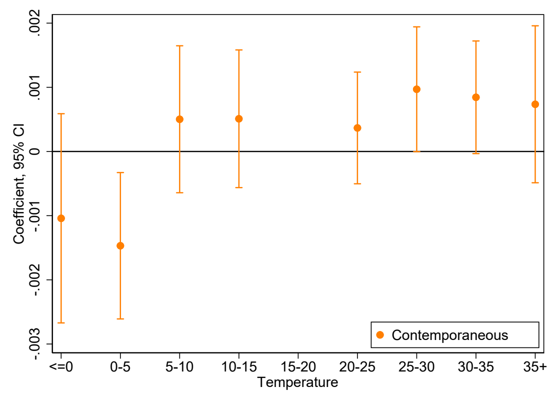
(a) Physical abuse



(b) Neglect



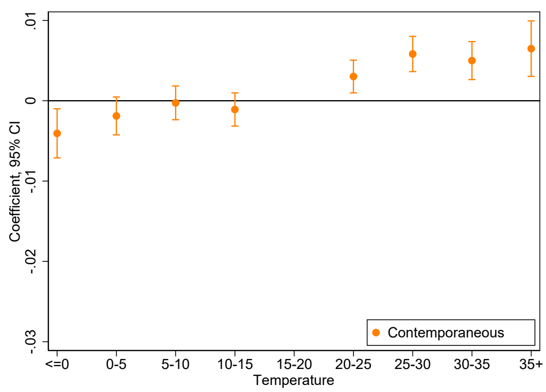
(c) Sexual abuse



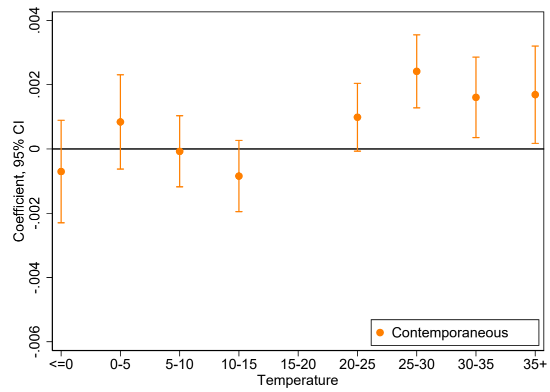
(d) Emotional maltreatment

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. For each panel, the results show the estimated relationship between temperature and the allegation rate where the rate is calculated by type of maltreatment. Panel (a) shows results for physical abuse; panel (b) shows results for neglect; panel (c) reports results for sexual abuse; panel (d) provides results for emotional or psychological maltreatment. The allegation rate is the number of children age 0-4 per 1,000 with at least one maltreatment allegation of the respective type during the county-period.

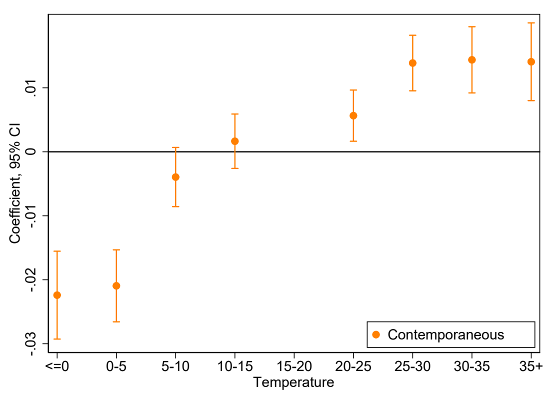
Figure A10: Relationship between Temperature and Maltreatment of Young Children by Prior Victim Status



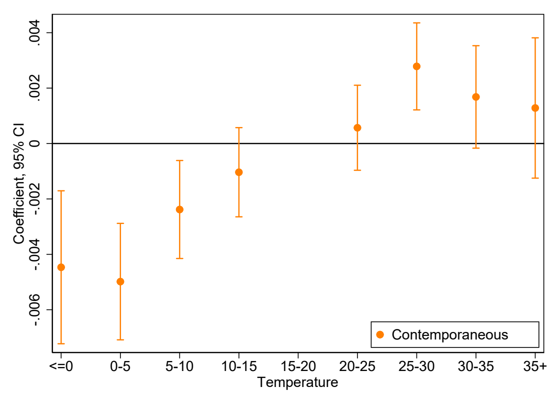
(a) Allegation rate, prior victim



(b) Victimization rate, prior victim



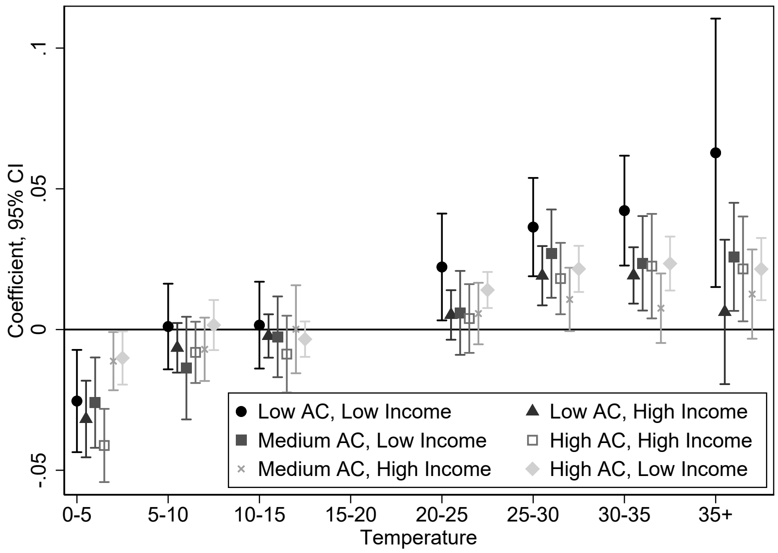
(c) Allegation rate, not prior victim



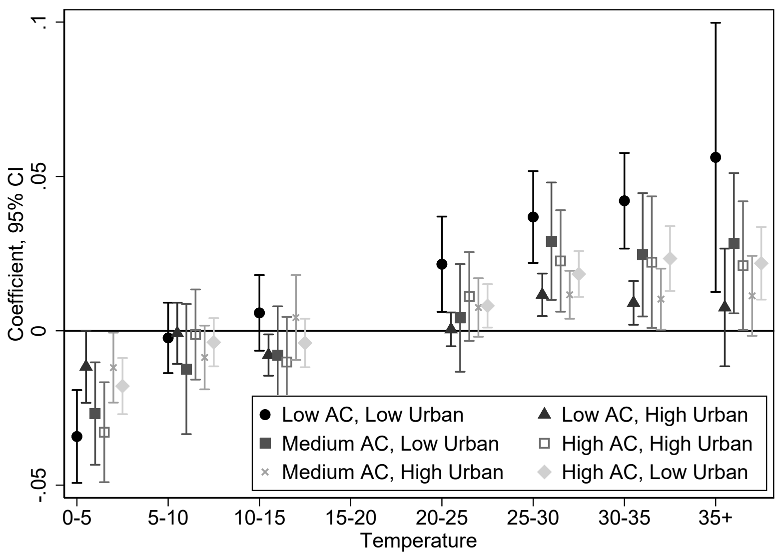
(d) Victimization rate, not prior victim

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Panels (a) and (c) plot results for the allegation rate, the number of children age 0-4 per 1,000 with at least one allegation during the county-period. Panels (b) and (d) show results for the victimization rate, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the county-period. The top panels depict results for children who are known to be prior maltreatment victims while the bottom panels show results for children who are not known to be prior victims of maltreatment

Figure A11: Relationship between Temperature and Allegation Rate of Young Children by Air Conditioning Penetration, Median Household Income, and Urbanicity



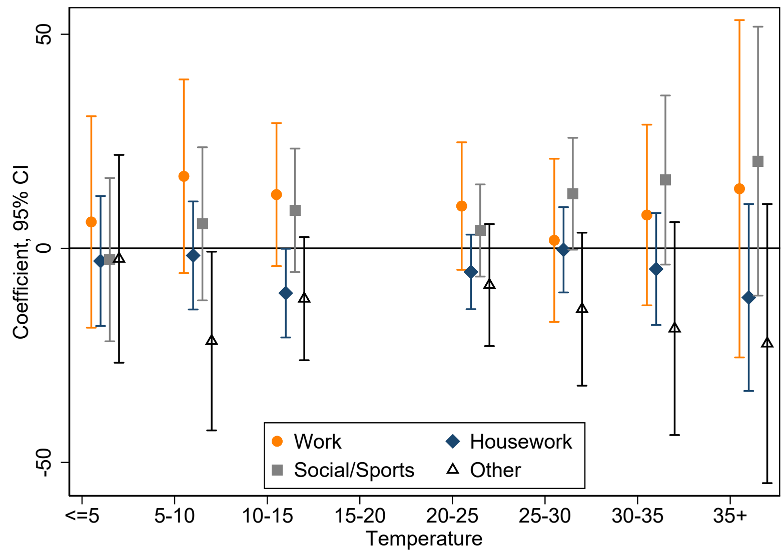
(a) Median household income



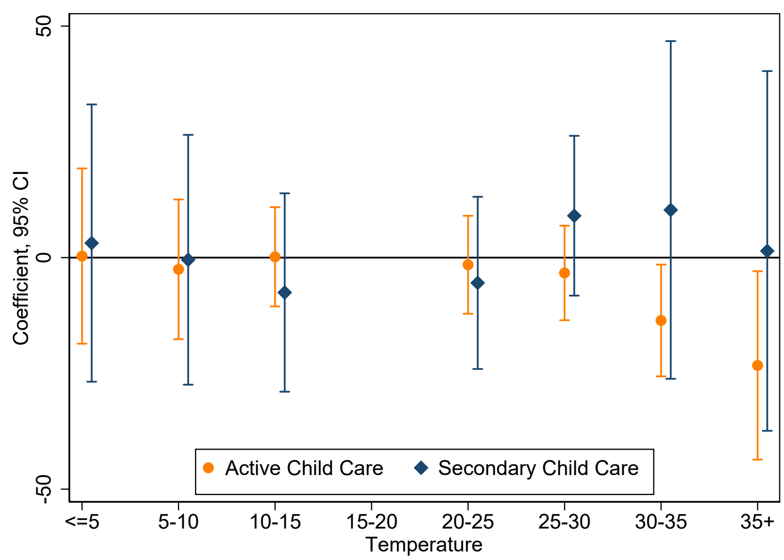
(b) Percent urban

NOTES: This figure plots estimated coefficients and sums of estimated coefficients as appropriate, and 95% confidence intervals. Panel (a) reflects a specification that includes interactions among the contemporaneous temperature bin variables and six indicators for types of counties by median household income (above/below median) and residential air conditioning penetration rate in 2005 (by tercile). Panel (b) is constructed similarly but reflects a specification with interactions among the contemporaneous temperature bin variables and six indicators for types of counties by urbanicity (above/below median) and residential air conditioning penetration rate in 2005 (by tercile). Dots indicate low-AC and low-income/urbanicity counties, triangles low-AC and high-income/urbanicity counties, squares medium-AC and low-income/urbanicity counties, hollow squares medium-AC and high-income/urbanicity counties, Xs high-AC and low-income/urbanicity countiesm, and diamonds high-AC and high-income/urbanicity counties. Temperature leads and lags are

Figure A12: Relationship between Temperature and Parental Time Use



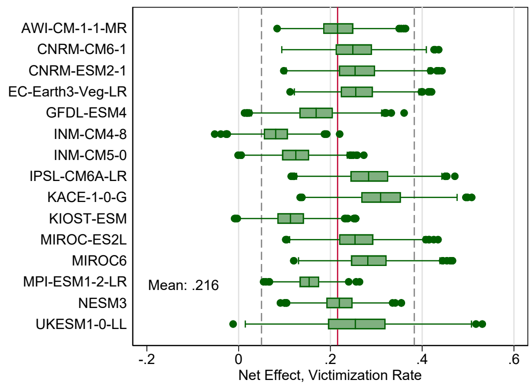
(a) General Activities



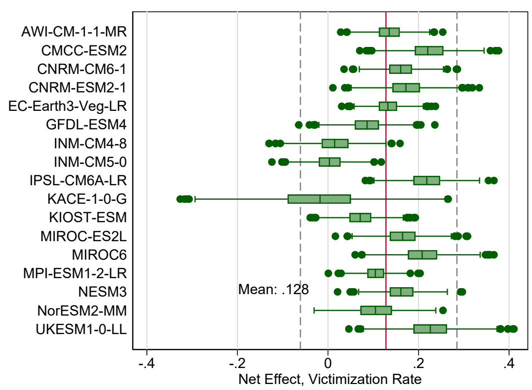
(b) Childcare

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Precipitation is included, as are fixed effects for county-bimonthly period, day-of-week, and state-year. The number of ATUS observations is 16,521. Mean values (standard deviations) for the time use variables, measured in minutes per day—Work: 182.5 (257.9), Housework 124.6 (130.4), Sports/Social: 224.6 (168.1), Everything Else: 907.5 (198.6), Active Childcare: 126.8 (130.9), Secondary Childcare: 402.9 (130.9)

Figure A13: Average Predicted Change in Victimization Rate for Young Children Due to Climate Change, Alternative Period and Sample



(a) In-sample Counties, 2081-2100



(b) US-wide Counties, 2040-2060

Notes: Panel (a) plots the estimated change in the victimization rate of children aged 0-4, that is the change in the average number of children per 1,000 with at least one substantiated maltreatment allegation, attributable to climate change in our sample counties in 2080-2100. Panel (b) plots the estimated change in the victimization rate of children aged 0-4, that is the change in the average number of children per 1,000 with at least one substantiated maltreatment allegation, attributable to climate change in the contiguous US in 2040-2060. Both panels reports results for 15 climate models across 1,000 bootstrap replications of our main specification. For each model, we report the minimum and maximum estimates obtained, alongside the median, as well as first and third quartiles. The vertical dashed gray lines report the 2.5^{th} and 97.5^{th} percentiles across all models and bootstrap replications (0.05 and 0.383, respectively), while the vertical solid line reports the overall mean, 0.216.

Table A1: Summary Statistics for Outcome Measures

	Mean (Standard deviation)
Panel A: Allegation rate measures	
Allegation rate	3.459 (2.100)
Allegation rate, professional source	1.757 (1.260)
Allegation rate, non-professional source	1.702 (1.321)
Allegation rate, prior victim	0.682 (0.830)
Allegation rate, not prior victim	2.573 (1.724)
Panel B: Victimization rate measures	
Victimization rate	0.792 (0.725)
Victimization rate, professional source	0.551 (0.526)
Victimization rate, non-professional source	0.240 (0.329)
Victimization rate, prior victim	0.209 (0.328)
Victimization rate, not prior victim	0.536 (0.528)
Panel C: Additional measures	
Substantiation rate	0.233 (0.143)
Foster care removal rate	0.194 (0.235)

Notes: Table reports means and standard deviations for outcome measures based on the balanced panel sample of 114,312 observations, which represents 433 unique counties for 264 bimonthly periods. The foster care removal rate mean and standard deviation are based on an unbalanced panel of 376 counties. See text at beginning of appendix for information on construction of measures.

Table A2: Results for Control Variables in Main Specifications

	Allegation rate	Victimization rate	Mean (Standard deviation)
Share of children in poverty	1.439**	0.0602	0.210
	(0.533)	(0.248)	(0.074)
Median household income (1,000 2016 USD)	-0.00931*	-0.00989***	54.994
	(0.00433)	(0.00224)	(13.047)
Share Black	5.059	1.470	0.120
	(3.286)	(1.552)	(0.120)
Share Hispanic	-10.59***	-2.932*	0.139
	(2.282)	(1.283)	(0.155)
Share other race	-15.57***	-2.453	0.045
	(3.821)	(1.580)	(0.052)
Unemployment rate	0.00911	0.00331	6.839
	(0.0185)	(0.00830)	(2.714)
Average daily precipitation over reporting period (in decimeters)			
Contemporaneous	-1.083***	-0.325***	0.028
	(0.147)	(0.0601)	(0.028)
Lag 1	0.182	0.00671	0.028
	(0.121)	(0.0602)	(0.028)
Lag 2	0.0856	0.000638	0.028
	(0.126)	(0.0536)	(0.028)
Lead 1	0.118	-0.0175	0.028
	(0.143)	(0.0595)	(0.028)
Lead 2	0.0484	0.0140	0.028
	(0.130)	(0.0591)	(0.028)

NOTES: First two columns of the table report the estimated coefficients and standard errors associated with control variables for the two main outcome variables: allegation rate and victimization rate. Fixed effects are as described in the main specification. The final column reports sample means and standard deviations. Socioeconomic controls are annual county-level measures. Sample size is 114,312. which represents 433 unique counties for 264 bimonthly periods.