Temperature and Maltreatment of Young Children*

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Abstract

We estimate the impacts of temperature on alleged and substantiated child maltreatment among young children using administrative data from state child protective service agencies. Leveraging short-term weather variation, we find increases in maltreatment of young children during hot periods. We rule out that our results are solely due to changes in reporting at high temperatures. Additional analysis identifies neglect as the temperature-sensitive maltreatment type, and we find limited 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.

Keywords: Child Maltreatment; Child Abuse and Neglect; Climate Change; Temperature;
JEL CODES: Q54; I31; J12; J13.

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1 Introduction

In the US, child maltreatment is common and costly; almost 40% of children in a 2011 survey reported experiencing maltreatment by adulthood (Finkelhor et al., 2013). Maltreatment is most prevalent among young children: in 2019, about 40% of victims of child maltreatment were between the ages of zero and four (Children's Bureau, 2021). Victims of child maltreatment have lower levels of educational achievement, lower rates of employment, lower earnings, fewer assets, an increased risk of substance abuse, and are more likely to engage in crime and be incarcerated later in life (Currie and Tekin, 2012; Currie and Spatz Widom, 2010; Cicchetti and Handley, 2019; Eckenrode et al., 1993; Lansford et al., 2002; Mersky and Topitzes, 2010; Widom, 1989; Zielinski, 2009). Fang et al. (2012) estimate an average lifetime cost per victim of nonfatal child maltreatment of over $200,000 (2010 USD).[1]

Assessing risk factors for child maltreatment to inform prevention efforts is a national research priority (Office of the US Surgeon General, 2005). A large literature in public health and sociology identifies a range of factors correlated with child maltreatment including poverty, parental mental health, and parental substance abuse, among others. Recent contributions to this literature speak to the potential impacts of climate change on child maltreatment by exploring links between natural disasters and child maltreatment, and exposure to extreme temperatures and child maltreatment. Curtis et al. (2000) and Keenan et al. (2004) find increased reports of child abuse and incidence of inflicted traumatic brain injury, respectively, following natural disasters. Gruenberg et al. (2019) conduct a retrospective chart review of pediatric emergency department admissions and document a correlation between heat and admissions related to child abuse. Using similar research methods, Mehta et al. (2022) find no evidence of disproportionate increases in abusive head trauma with higher temperatures.

Motivated by findings in physiology and psychology, a growing literature in economics

[1]The estimate reflects healthcare costs, productivity losses, child welfare costs, criminal justice costs, and special educational costs.

identifies several channels through which extreme temperatures might affect actual and/or observed child maltreatment. First, hot temperatures may make adults more aggressive or children more restless through physiological channels (Hsiang et al., 2013; Ranson, 2014; Heilmann et al., 2021; Baylis, 2020; McCormack, 2023). Second, extreme cold and hot temperatures are known to affect time use for children and adults (Graff Zivin and Neidell, 2014; Cosaert et al., 2023a,b; Cohen and Gonzalez, 2024). Changes in time use may result in adults and children spending more time together in confined spaces, perhaps leading to increased parental stress or inattentive care; or may change the likelihood of maltreatment being witnessed and reported. Third, heat reduces cognitive function and adversely impacts mental health (Taylor et al., 2016; Graff Zivin et al., 2018; Park, 2022; Park et al., 2020; Mullins and White, 2019), which may alter parental decision making.

Finally, extreme temperatures can create an environment in which caregiver behaviors, themselves potentially influenced by temperature as discussed, lead to increased risk of harm for children under their care. An illustrative example is the case of children left unattended in vehicles, which results in dozens of heatstroke deaths each year in the U.S. (Levenson, 2023). Deaths occur when caregivers unknowingly or intentionally leave children unattended in vehicles, or when children gain access to vehicles on their own unbeknownst to their caregivers. Not surprisingly, a majority of these deaths occur at hot temperatures. Notably, however, the distribution of temperature varies with the underlying circumstances surrounding the deaths. Figure 1 shows that deaths resulting from intentional parental actions happen at lower temperatures compared to deaths resulting from accidental parental inattention.[2] While not causal, this pattern underscores the complex interactions among caregiver attentiveness and behavior, risks for children, and extreme temperatures to which our paper speaks.

Specifically, this paper sheds light on the relationship between temperatures and child

[2]Data reflects deaths between 2001 and 2022. Data source: Jan Null, CCM, Department of Meteorology and Climate Science, San Jose State University, http://noheatstroke.org. The authors thank Jan Null for providing access.

welfare by estimating the impacts of short-term variation in temperatures on alleged and substantiated maltreatment of young children ages zero to four–those most vulnerable to maltreatment. We use data from the National Child Abuse and Neglect Data Systems (NCANDS) Child Files, an administrative census of reported maltreatment to state child protective service (CPS) agencies that received a CPS response (over half of maltreatment reports). We form measures of alleged and substantiated child maltreatment by bimonthly period from 2006 to 2016 for each county in our sample.

To measure temperature variation, we use modeled gridded daily weather data from the PRISM Climate Group at Oregon State University. For each bimonthly period, we count the number of days in which the maximum temperature falls within given ranges to isolate cold and hot days and allow the effect of temperature to be nonlinear. We focus on the daily maximum as a proxy for temperatures during active hours. Our empirical strategy exploits variation across years within US counties in bimonthly-period temperatures. This allows us to control for county-specific seasonal patterns. For example, variation in treatment might be driven by an unusually hot early-July period for a particular county. We also include state-year fixed effects to absorb policy variation and other changes at the state-year level and reporting-period fixed effects to absorb national idiosyncratic shocks.

We find increases in both alleged and substantiated maltreatment of young children during hot periods (with maximum temperatures greater than 20° Celsius or 68° Fahrenheit). In particular, we estimate that an additional day of extreme heat (>35°Celsius) in a county and bimonthly period increases maltreatment by half of a percent relative to a day with maximum temperature 15-20° Celsius. We find that these effects are concentrated in the category of child neglect, rather than physical or sexual abuse, which suggests that changes in parent and child time use, parental cognitive capacity, and attentiveness are likely relevant mechanisms. Indeed, in supplemental analysis using the American Time Use Survey we find reductions in parental time spent on active childcare during hot periods. At the other end of the temperature distribution, our results for cold temperatures imply both a lower likelihood of maltreatment on colder days and reductions in reporting with a pattern suggestive of increases in the marginal severity of cases reported at colder temperatures. Notably, our findings at both ends of the temperature spectrum related to child neglect, match the pattern of association between temperature and emergency department visits for both accidental injury and poisoning found in Gould et al. (2024).[3]

Our work identifies a novel channel through which climate change will adversely impact child welfare. In particular, our results suggest that *acute* child neglect, defined as causing or threatening to cause serious harm to a child, will increase as temperatures rise. Combining predictions from 15 global climate models and 1,000 bootstrap replications in a back-of-the-envelope calculation, we estimate that over the period 2081-2100, climate change will lead to an annual average increase in the number of young children with a substantiated maltreatment case per county of 1.53% over the 2016 mean, with over 95% of our 15,000 estimates being positive. Importantly, we do not find evidence that effects of temperature vary across climate zones, and we find limited evidence that air conditioning mitigates the temperature-maltreatment relationship. These patterns suggest that adaptation to climate change might not be sufficient to undo these negative predicted effects.

2 Background

2.1 Defining and measuring child maltreatment

Child maltreatment refers to all types of abuse and neglect of children under age 18 by an adult serving in a custodial role (e.g., parent, caregiver, coach, clergy). In the US, federal legislation, state civil statutes, and state criminal statutes provide formal definitions of child maltreatment. At the federal level, the Child Abuse Prevention and Treatment Act (CAPTA) (42 U.S.C.A. Â§ 5106g), originally enacted in 1974, identifies a set of acts that

[3]See Figure 5 in Gould et al. (2024). The study does not focus on children and does not explicitly discuss child maltreatment. However, the authors acknowledge that the majority of emergency department visits in their data are among young children.

constitute child maltreatment:

> at a minimum, any recent act or failure to act on the part of a parent or caretaker, which results in death, serious physical or emotional harm, sexual abuse or exploitation, or an act or failure to act which presents an imminent risk of serious harm.

CAPTA provides guidance and funding to states to support their efforts related to child maltreatment including prevention and response.[4] Definitions of child maltreatment in state civil statutes permit intervention by state CPS agencies while criminal statutes provide grounds for arrest and prosecution of offenders.

Child maltreatment is most prevalent among children under age one and 25% of child maltreatment victims are under age three (American Academy of Pediatrics, 2022). Victimization rates are higher among American-Indian and Alaska Native children, and among Black children compared to children of other races and ethnicities. Most victims of child maltreatment, about 70% in 2019, are first-time victims (Children's Bureau, 2021).

Most states recognize four types of child maltreatment: physical abuse, neglect, sexual abuse/exploitation and emotional abuse. Specific definitions of child maltreatment within these categories vary across states.[5] Among types of child maltreatment, neglect is the most complex and most common, accounting for over three-fourths of substantiated cases of child maltreatment in the US in 2020 (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. As with child maltreatment more generally, state statutes vary in their definitions of neglect (Children's Bureau, 2018a). The most commonly recognized categories of neglect include physical neglect (e.g., failure to provide basic needs like nutrition or hygiene); medical neglect (e.g., failure to provide adequate medical care); emotional neglect (e.g., failure to provide emotional support, exposing a child to intimate partner violence or substance use); inadequate supervision (e.g.,

[4]See Children's Bureau (2019a).

[5]Children's Bureau (2022) provides more detailed information on variation in civil definitions of child maltreatment across states.

leaving young children home alone, leaving children with inappropriate caregivers); and educational neglect (e.g., failure to enroll a child, chronic absenteeism).

A finding of neglect can result from a single incident of the above. Leaving a young child alone in a car, allowing a young child to wander near a busy street, and allowing a child unattended access to drugs or poisonous substances are examples of acute neglect. In other cases, neglect is chronic, resulting from a caregiver repeatedly failing to meet a child's basic physical, developmental, and/or emotional needs over a period of time (Children's Bureau, 2019b). For our purposes acute neglect is the most relevant category, as it is the category that is likely to respond contemporaneously to changes in temperature.

CPS referrals come from various sources including non-professionals (e.g., neighbors, family members) and professionals with whom children interact (e.g., teachers, physicians). 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, 2019c). Most frequently these include social workers, healthcare professionals, law enforcement officers, and educational and childcare personnel. Once received, CPS evaluates whether or not a referral meets agency criteria for an investigation or alternative response (e.g., provision of services). If so, then the referral is "screened in."[6] In 2019, about 54% of CPS referrals were screened in. Once a referral is screened in, it is referred to as a report. In 2019, almost 70% of reports were submitted by professional sources (Children's Bureau, 2021). After investigation by the CPS agency, the report receives a disposition. If the report disposition finds that the alleged maltreatment is substantiated or indicated, then the child or children on the report are considered to be victims of child maltreatment.

Because the true amount of child maltreatment is unobserved, measurement is an important consideration when studying 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

[6] According to Children's Bureau (2021), referrals are screened out if a response by another agency is more appropriate, or if the referral does not contain sufficient information, among other reasons.

of child maltreatment (Lindo and Schaller, 2014). Bald et al. (2022) emphasize that prevalence measures based on administrative data only reflect child maltreatment reported to CPS agencies.[7] Bullinger et al. (2021) underscore the importance of addressing potential sources of measurement error in administrative data, in particular when making comparisons across states and across times due to the potential for important sources of cross-sectional and temporal variation in child maltreatment measures. For example, the definition of maltreatment and the processes for reporting suspected maltreatment may vary across states and within a state over time. In addition, children's exposure to potential mandatory reporters may vary over calendar time and over their lives. For example, school-aged children are more likely to be exposed to mandatory reporters when they are in school (e.g., during the school year as opposed to over summer break).[8]

2.2 Potential mechanisms

Potential mechanisms linking ambient temperature and measured child maltreatment fall into three categories: (1) effects of temperature on the cognition, mental health and behavior of adults and children, (2) effects of temperature on child and parental time use, and (3) effects of temperature on children's exposure to potential professional or nonprofessional reporters, including CPS workers, police officers, medical providers, teachers, neighbors, and childcare providers. Changes in behavior (such as aggression) and time use (such as parents' work hours) will lead to changes in the true incidence of child abuse and neglect (Bullinger et al., 2021), while changes in exposure to reporters would change the likelihood that a given incident is reported and reflected in our data. In considering potential channels, we can also differentiate between factors that might lead to physical abuse of a child, such as adult aggression, economic stress, or child behavior; and factors that might lead to acute neglect,

[7] Bullinger et al. (2021) discuss additional advantages and disadvantages of administrative data for measuring child maltreatment compared to other potential data sources.

[8] Benson et al. (2022) explore child maltreatment reporting by educational professionals. Their results suggest that more time spent in school increases reports of child maltreatment and that the increased reporting by educational professionals represents new, high-quality reporting as opposed to over- or duplicate reporting.

including adult cognitive capacity, childcare decisions, and environmental risk factors like outdoor play and hot cars.[9]

Numerous studies have documented that high temperatures lead to increases in violence, criminal activity, and aggression among adults, causing increases in both inter-group and interpersonal conflict (see Burke et al. (2015b) for a review). Proposed mechanisms for this association include biological and economic stressors and also changes in activities and time use. McCormack (2023) finds that children experience more disciplinary referrals at school when the weather is hot, suggesting that children's behavior, and/or teachers' tolerance of children's behavior, might also be adversely affected by warm temperatures. Meanwhile, cold temperatures have been found to have adverse effects on adult mental health and well-being (Janzen, 2022; Baylis, 2020), but seem to have a chilling effect on violence and criminal activity, perhaps from reduced activity and social interaction (Ranson, 2014). While few studies have considered the association between temperature and violence toward children, Henke and Hsu (2020) find that hot temperatures increase intimate partner violence (IPV) and Sanz-Barbero et al. (2018) find increases in intimate partner femicide in the days following heat waves. Increases in IPV could directly lead to reported and substantiated child maltreatment and could also cause families to have more encounters with law enforcement, which could result in more reporting of existing child maltreatment.

With respect to parental decision-making and child neglect, Almås et al. (2019) and Taylor et al. (2016) document that thermal stress from extreme temperatures affects judgment, decision-making, and cognitive capacity. Importantly, extreme temperatures increase the potential degree of danger associated with poor parenting decisions. For example, extreme heat and cold cause unsafe conditions for leaving a young child alone in a car; thus, doing so may increase the likelihood of a maltreatment referral if the weather is extreme but not when temperatures are moderate. Hot car deaths, in particular, occur annually in the US and are concentrated entirely among children under the age of five (kidsandcars.org, 2023).

[9]Chronic child neglect, while an important component of maltreatment, is unlikely to immediately respond to contemporaneous changes in temperature, so we focus here on the determinants of acute neglect.

Moreover, when the weather is warmer, parents may also allow young children to play outside without adult supervision, and children could wander into traffic or be lost, resulting in police reports and acute neglect allegations.

In addition to direct changes in behavior and parenting capacity, there may also be indirect changes in the incidence of neglect and abuse that occur because temperature alters parent and child time use. For example, McCormack (2023) shows that school absences increase in warmer temperatures. Parental labor supply might also change, which could affect maltreatment by affecting the time that parents spend with children (Lindo et al., 2018; Price and Wasserman, 2023). Changes in time use may also result in changes in exposure to potential reporters of maltreatment by changing the degree of interaction with friends, neighbors, teachers, doctors, law enforcement, and even CPS workers. For example, in warm weather, families may spend more time outdoors in public places (e.g., parks and playgrounds). During colder weather, families may be confined indoors in their own homes, interacting less frequently with potential reporters. In line with this story, Cosaert et al. (2023a) document that cold temperatures lead to reduced time spent with friends, while increasing time spent with family. As further suggestive evidence, multiple studies find reductions in non-essential emergency department visits at cold temperatures (Davis et al., 2020; Gould et al., 2024; Mullins and White, 2019).

The extent to which these various channels operate depends on a range of factors, including child age. First, most children ages four and under are not yet enrolled in school and thus are less likely to be exposed to the seasonal patterns of involvement with educational personnel, who are an important source of mandatory reporting (Benson et al., 2022). Second, compared to older children, young children are more dependent upon parents to ensure their safety and meet their basic needs. As a result of their dependence, the same parental action for a young child may involve significant risk of harm to the child, and therefore potential child maltreatment, but only minimal risk for an older child (e.g., allowing a child to play outside without supervision, leaving a child alone in a car). Third, some physical injuries (e.g., fractures) that might arise due to accidents or abuse are more common among older children who are more mobile.[10] Thus, identifying maltreatment as the likely source of some physical injuries for older children may be more challenging compared to younger children. By focusing on young children, we aim to distinguish a temperature-child maltreatment relationship from merely a temperature-reporting of child maltreatment relationship.

3 Data

To explore the relationship between exposure to extreme temperatures and child maltreatment, we combine data from two primary sources, the National Data Archive on Child Abuse and Neglect (NDACAN) and the PRISM Climate Group. Data from the former allow construction of child maltreatment outcomes while the latter provide weather information.

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.[11] For a given year, the NCANDS Child File represents a census of screened-in CPS referrals that received a disposition in the federal fiscal year. State reporting under NCANDS is voluntary but most states and the District of Columbia consistently report during our study period. We use the NCANDS Child Files for fiscal years 2006-2018. These data contain case-level information, where a case denotes a report-child pair. For cases that appear in multiple Child Files,

[10] U.S. Department of Justice guidance to law enforcement on investigating potential child physical abuse identifies "injuries on children who are not mobile" and "injuries that routine, age-appropriate supervision of the child should have prevented" as red flags that necessitate further scrutiny (Farley et al., n.d.).

[11] The NCANDS Child Files (FFY2006v5, FFY2007v6, FFY2008v5, FFY2009v6, FFY2010v5, FFY2011v5, FFY2012v5, FFY2013v5, FFY2014v4, FFY2015v4, FFY2016v3, FFY2017v1, FFY2018v2) were provided by NDACAN at Cornell University, and have been used with permission. 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, U.S. 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.

we follow the recommendation in the NCANDS User's Guides to keep only the instance in the most recent fiscal year. For each case, we then identify the calendar year in which the suspected case was reported to the state CPS agency (as opposed to the fiscal year in which the case received a disposition) and focus on cases reported between 2006 and 2016. 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 or 2007 Child Files). Thus, collectively the Child Files for 2006 through 2018 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 geographic identifier available in the data is county. Furthermore, county identifiers are available only for cases coming from counties with at least 1,000 total cases in the fiscal year. Additionally, county is masked in the event of a child's death. Second, we observe the bimonthly period, between the 1$^{\text{st}}$ and 15$^{\text{th}}$ days of the month or between the 16$^{\text{th}}$ and the end of month, during which the report of child maltreatment was made. The exact report and incident dates are masked.[12] Given these features of the data, we form a balanced county-by-bimonthly period panel representing 433 counties in 42 states in the contiguous US for which we have daily weather data. Each county in the panel appears in all Child Files between 2006 and 2018. 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-bimonthly period level. The allegation rate is the number of children ages 0 to 4 per 1,000 with at least one screened-in child maltreatment report in the county-bimonthly period. The victimization rate reflects the number of children age 0 to 4 per 1,000 considered to be victims of child maltreatment in the county-bimonthly

[12] 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.

period. A child is considered to be a victim if a maltreatment allegation is determined by investigation to be substantiated or indicated according to the definition under state law. Annual child population data by county is from the Surveillance, Epidemiology, and End Results (SEER) Program. We use additional information available in NCANDS to further refine the child maltreatment measures, focusing on type of abuse and reporter. Summary statistics for all maltreatment measures are presented in Table A1. Changes over our sample period in the allegation and victimization rates for children ages 0 to 4 are presented in Figure A1, which depicts patterns similar to those for all children documented by Evans et al. (2022). The annual average allegation rate increases over the sample period while the annual average victimization rate declines until about 2013.

Maltreatment patterns vary seasonally (Figure 2a). Both maltreatment measures are generally lowest during the winter months. Importantly for our analysis, the raw data reveal differences in the seasonal pattern of allegation and victimization rates based on report source suggesting that, even for the young children we consider, exposure to different types of potential reporters varies throughout the year. During the summer months, allegations from professional report sources fall while those from non-professional report sources rise (Figure 2b). The pattern is similar but less stark for the victimization rate (Figure 2c).

Figure A2 shows spatial variation across sample counties in the median victimization rate for young children between 2006 and 2016. Among sample counties, victimization rates are highest in counties in New York and Massachusetts. According to Children's Bureau (2021) Kentucky and West Virginia had the highest victimization rate (for children of all ages) among US states in 2019; victimization rates for New York and Massachusetts were about twice the national average. Because of the NCANDS masking convention, few counties in Kentucky and West Virginia (i.e., less populous states) are represented in our sample. Noting this feature, the spatial pattern of victimization depicted in Figure A2 is broadly consistent with state-level variation documented elsewhere.

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).[13] 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.[14][15] Our results are robust to alternative construction and assignment of weather variables, as discussed below. Following related work (e.g., Barreca and Schaller (2020), Park et al. (2020)), we focus on daily maximum temperatures. For each county, we count the number of days in the bimonthly 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 construct a precipitation variable that reflects 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 use these data to create county-by-year control variables including those measuring race and ethnicity (e.g., share Black, share Hispanic) and economic conditions (e.g., share of children in poverty, median household income, unemployment rate). Appendix Table A2 provides summary statistics for control variables.

[13] Daly et al. (2002) note that observational weather can be sparse and unrepresentative while Park et al. (2020) note potential endogeneity concerns arising from correlations between the availability of monitoring stations and local economic or climate conditions. See Baylis (2020) and Dundas and von Haefen (2020) for recent environmental economics applications of the PRISM data.

[14] The median county in our dataset has four weather stations providing daily temperature data underlying the PRISM modeled data. Twelve counties have no weather station. The median station in sample counties had valid temperature data for 3,276 days out of the 4,018 days in our sample period.

[15] To construct population weights we use 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, we estimate high dimensional fixed effects models of the following form

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

where Y_{it} denotes the child maltreatment outcome in county i and bimonthly reporting period t. The variable N Days with $\text{MaxTemp}_{\text{it}}$ in Bin_j counts the number of days in county i during reporting period t in which the daily maximum temperature lies within 5-degree Celsius bin j. The model also includes two reporting 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 bimonthly reporting period t as well as two reporting period leads and lags of precipitation. $Z_{iy(t)}$ denotes a set of county-by-year controls. We include county-by-bimonthly 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. We cluster standard errors at the county level.

Figure 3 plots the estimated coefficients and 95% confidence intervals on three sets of temperature variables: (1) those associated with contemporaneous exposure (i.e., the estimated coefficients of primary interests), indicated by circles; (2) those associated with lagged exposure, represented as diamonds; (3) those associated with future exposure (i.e. leads), denoted with triangles. Panel 3a shows results for the allegation rate while panel 3b depicts results for the victimization rate. The excluded temperature variable indicates temperatures between 15 and 20 degrees Celsius (or 59 to 68 degrees Fahrenheit). In both panels, most of the estimated coefficients on leads and lags of temperature are not statistically different from zero. However, compared to moderate temperatures, contemporaneous exposure to cold and hot temperatures is associated with changes in both maltreatment measures. The nature of the relationships is different, with lower maltreatment at cold temperatures and higher maltreatment at hot temperatures relative to moderate temperatures. Maltreatment is especially low in the lowest two temperature bins, and especially high above about 25°C, with a weaker, roughly-linear relationship in between. We explore this pattern in more detail in the next section.

Table A2 provides estimated coefficients and standard errors for socioeconomic and precipitation control variables. Our results are broadly consistent with the literature; we find increases in the allegation and victimization rates associated with lower median household income. A higher share Hispanic is associated with lower allegation and victimization rates. We do not find a statistically significant relationship between the overall unemployment rate and child maltreatment.[16] A one standard deviation increase in contemporaneous precipitation is associated with about a 0.01 standard deviation decrease in both outcomes. We find no relationship between immediate past and future precipitation and child maltreatment.

The first column of Table 1 reports the estimated coefficients on the highest temperature bin variable, 35+ degrees Celsius, based on the contemporaneous exposure measure (i.e., the rightmost circles in panels (a) and (b) of Figure 3). Standard errors clustered at the county level are reported in parentheses while standard errors clustered at the state level are reported in brackets for comparison.[17] For the allegation rate model 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-bimonthly reporting period associated with shifting the daily max-

[16]This is consistent with Lindo et al. (2018).

[17]Standard errors clustered at the state level account for additional spatial correlation across counties within states that might be introduced, for example, due to modeling of weather data.

imum temperature on one day in the reporting period from the reference temperature bin (i.e., 15 to 20°C) to the highest temperature bin (i.e., at or 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 from the 15-20°C range to above 35°C in one bimonthly reporting 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 bimonthly reporting 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. As we might expect given our focus on temperature, the effects we estimate are more modest.

The remaining columns of Table 1 explore robustness of the results reported in column (1). 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. Column (8) explores robustness of our results to an alternative sample to address concerns about the selected nature of the sample (i.e., due to the NCANDS masking convention). To form the alternative sample, we begin with the 3,140 counties for which we have child population measures from SEER for 2006, the first year of the sample period. In 2006, the mean county has an estimated population of about 6,350 children ages 0 to 4. 568 counties have child populations that exceed the mean and 349 of these counties (about 61%) show up in our original sample. These 349 relatively large counties in terms of young child population comprise the alternative sample. Thus, the alternative sample excludes smaller counties that show up in the NCANDS data, and therefore in our main sample, merely because they have a large amount of child maltreatment.[18] Results with this alternative sample are similar to our main results.

We conduct several exercises to explore the sensitivity of our results to how we measure temperature. First, we consider coarser and finer temperature bins. In particular, in panels (a) and (c) of Figure A3 we define bins of 10°C: below 0, 0-10, 10-20 (the omitted category), 20-30, and higher than 30. The estimated coefficients are similar those in Figure 3, suggesting that our main results are not an artifact of sparsely populated bins. In panels (b) and (d), we instead use finer bins of 3°C spanning the range from below 0 to above 36°C, with 15-18 as the omitted category. Effects appear to increase with temperature until they plateau for temperatures above about 27°C.

Second, instead of relying on the population-weighted spatial average of weather variables as we do for our main results, we use the area-weighted spatial average. Figure A4 shows that using temperature bins and precipitation controls constructed from these averages does not affect our estimates in a meaningful way. Finally, we re-estimate our main model by 2003 International Energy Conservation Code (IECC) climate zones to explore whether habituation to warmer temperatures alters the temperature-maltreatment relationship.[19] Figure A5 report 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 3 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

[18]These smaller counties may be less representative of similarly sized counties with lower levels of child maltreatment and therefore may threaten the external validity of our results.

[19]We combine zones to facilitate more balance among the sub-samples. Specifically, we treat zones 1 (very hot humid/very hot dry) and 2 (hot humid/hot dry) as a single zone. We also combine zones 5 (cool humid/cool dry/cool marine), zone 6 (cold humid/cold dry), and zone 7 (very cold) as a single zone. Zone 3 (warm humid/warm dry/warm marine) and zone 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.

habituation does not substantially alter the relationship between hot temperatures and child maltreatment.

4.1 Evidence on mechanisms

In this section, we conduct additional analyses to shed light on the mechanisms through which temperatures affect maltreatment. 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 the types of counties where the temperature-maltreatment relationship is stronger. 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

First, we use available information on child and case characteristics to investigate the roles of reporting and previous CPS interactions. To assess whether hotter temperatures 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 marginal severity of reported cases. This would result in variation in the substantiation rate with temperatures. Figure 4 depicts the estimated relationship between contemporaneous temperature and the substantiation rate.[20] The estimated coefficients on the hot temperature variables are close to zero and statistically insignificant, suggesting that our results for high temperatures do not merely reflect changes in the reporting of child maltreatment. The results for cold temperatures are noisier but illustrative of increased substantiation rates for the lowest temperatures bins. This pattern is consistent with an increase in the marginal severity of

[20]The model includes the temperature lead and lag variables but they are excluded from this and following figures to highlight the estimated coefficients of interest.

reported maltreatment cases at colder temperatures (i.e., less severe cases are more likely to go unreported at cold temperatures).

We can also 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 any bias that arises from the physiological impacts of heat exposure. If so, then we would observe a different pattern for the relationship between temperature and child maltreatment, depending on the source of the maltreatment report. We explore this question by differentiating between professional and non-professional report sources. Professional reporters include educational, law, and medical personnel. Non-professional reporters include neighbors, friends, etc.[21]

Figure 5 shows results, focusing on the estimated coefficients and 95% confidence intervals for the contemporaneous temperature variables. 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 increased child maltreatment at higher temperatures with estimated coefficients within each panel that are relatively similar in magnitude beyond 25°C. However, at cold temperatures, there are differences across reporting categories. For outcomes based on professional reports, the estimated temperature-maltreatment relationships shown in Panels 5a and 5b appear linear at cold temperatures—there are fewer allegations during the coldest periods and also fewer substantiated victims. For non-professional reporters, the allegation rate (Panel 5c) also falls at cold temperatures, but there is no corresponding statistically significant reduction in victimization rates (Panel 5d), suggesting that the reduction shown in Panel 5c reflects reporting of duplicate cases or cases that eventually would not be substantiated.

Next, we 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

[21] See the appendix for more details on the specific types of reporters included in the two categories.

periods could be associated with increases both in physical abuse and in neglect deriving from caregiver actions that might endanger the child. The channel linking exposure to extreme temperatures and sexual abuse is less clear. Figure 6 shows the estimated relationship between contemporaneous temperature and the victimization rate for three types of child maltreatment: physical abuse, neglect, and sexual abuse.[22] Notably, we find no evidence of increased victimization rates for physical or sexual abuse at high temperatures (Figures 6a and 6c, respectively). Rather, Figure 6b shows that the estimated effects of hot and cold temperatures on maltreatment of young children reported in Figure 3 are driven by increased neglect, the most common maltreatment type. As acute neglect occurs when children are left or put in a potentially harmful situation, this suggests that changes in parental time spent caring for children, attentiveness to childcare, and cognitive capacity might be key mechanisms. Examples of acute neglect include a young child being left in a hot car, being left unattended around a weapon, ingesting poison, or wandering onto a busy street.

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 children of CPS engagement are substantial, in particular for Black children (Roberts, 2022). If these costs outweigh benefits for some victims, 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.[23] Figure 7 shows that, compared to moderate temperatures, higher temperatures generally increase child maltreatment 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

[22]Figure A6 shows results for the allegation rate.

[23]The NCANDS variable we use for this information is missing for about 15% of the child-level sample; children with missing values are not reflected in the child maltreatment measures we use for this component of our analysis.

prior CPS exposure (Panel 7b).[24]

4.1.2 From county socioeconomic characteristics

Prior work on the relationship between exposure to extreme 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).[25] In the median US county in 2005, 74% of households have air conditioning according to this measure. We create an indicator variable for counties with penetration rates above this value and then create interactions between this indicator variable and the contemporaneous temperature bin variables. We include these interactions in the main specification allowing for the relationship between contemporaneous temperature and child maltreatment to vary based on air conditioning penetration. Figure 8 reports the estimated coefficients and 95% confidence intervals for the contemporaneous temperature variables, which reflect the estimated effects of contemporaneous binned temperature in counties with below-median air conditioning penetration in 2005 (circles); and sums of these estimated coefficients and those on the interaction terms, which together capture estimated effects of contemporaneous binned temperature in counties with above-median air conditioning penetration (diamonds). We do find some evidence of differential effects by air conditioning penetration at the highest temperatures.[26] However, the difference is not statistically significant. Thus, at least based on this historical measure, we fail to detect a clear moderating impact of air conditioning.[27] Our finding of limited adaptation via air conditioning in the child maltreatment context is consistent with

[24] Figure A7 shows results for the allegation rates.

[25] We thank Jisung Park for his willingness to share these estimates.

[26] Results for the allegation rate, presented in Figure A8, show no substantial differences in the temperature-allegation rate relationships for counties below and above the median air conditioning penetration rate.

[27] Motivated by Chirakijja et al. (2024) who find a link between heating prices and winter mortality, we also explore heterogeneity by energy prices, for which we have variation at the state-month level. Figure A9 shows no substantial differences in the estimated temperature-maltreatment relationship between county-periods with relatively higher versus lower energy prices.

Mullins and White (2019), who estimate a similar relationship between temperature and mental health outcomes across different levels of air conditioning penetration.

As a final exercise, we explore effect heterogeneity by socioeconomic variables at the county level. Specifically, we construct interactions between our temperature bin variables and indicators for a county having above-median values of each of three economic control variables measured in 2006 (i.e., the first sample year): median household income, share of children in poverty, and the unemployment rate. Figure A10 reports the estimated coefficients and 95% confidence levels on the contemporaneous temperature bin variables, which reflect the estimated effects in counties with below-median values (circles); and sums of these estimated coefficients and those on the interaction terms, which together capture estimated effects in counties with above-median values (diamonds). In panels A10a (allegation rate) and A10b (victimization rate), the estimated coefficients on the high temperature bin variables are generally larger for counties with below-median household income. A similar pattern appears in panels A10c and A10d. By contrast, the estimated coefficients in counties with below- and above-median unemployment rates are closer in magnitude (Panels A10e and A10f). However, along all three dimension, we are not able to statistically distinguish between the estimated effects in below- and above-median counties.

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 this channel directly, we use data from the American Time Use Survey (ATUS).[28] 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 ac-

[28]We obtained this data from IPUMS (Flood et al., 2024).

tive 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-bimonthly fixed effects, state-year fixed effects, and day-of-week fixed effects. Results from this exercise are presented in Appendix Figure A11. Panel A11a does not show any statistically significant changes in parental time use spent in any of the three general categories for either hot or cold temperatures, though there is some indication that time spent on sports and leisure may increase at hot temperatures. Panel A11b shows that there also are no significant changes in provision of secondary childcare. However, Panel A11b does show significant decreases in time spent on *active* childcare in the warmest temperature bins, suggesting that parents may indeed be less attentive to their children when it is hot.

5 Impact of Climate Change on Child Maltreatment

This section performs a back-of-the-envelope calculation to predict the change in child maltreatment in US counties under a plausible, non-worst case, climate change scenario. For this exercise, we focus on the victimization rate. We require two inputs. First, our results in Figure 3b show the estimated effect of shifting the maximum temperature for one day in the county-bimonthly reporting 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; these are the $\hat{\beta}$s we will use in this exercise. Second, we compute future maximum daily temperatures by county in order to predict changes in the number of days with maximum temperatures in each bin for each county-bimonthly period, denoted $\mathbf{\Delta C}$. Multiplying these two objects, we obtain estimates of the net effect of climate change on the victimization rate in the US under the assumptions that the temperature-maltreatment relationship will remain constant and that the temperature-maltreatment relationship we estimate extends to US counties not included in our sample. The first assumption presumes that no policy that could mitigate this relationship is adopted. The second assumption relates to the comparability of our sample and those counties that are excluded due to masking issues.

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 2081-2100 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.[29] 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 bimonthly periods corresponding to our reporting periods in an average year in 2081-2100. 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. (2015a) and bootstrap our main specification sampling observations 1,000 times with replacement. We then multiply each of these 1,000 sets of $\hat{\beta}$s by the $\Delta\mathbf{C}$ obtained from each of the 15 climate models, to allow for uncertainty in the climate projec-

[29] 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).

tions. Thus, this exercise yields a vector of 15,000 bootstrap replications for each county, which reflect both sources of uncertainty.

Figure 9 plots the results of this exercise, extrapolating to 3,109 counties in the contiguous United States for which we have climate data.[30] 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. We display the uncertainty inherent in this exercise by plotting the range of estimates obtained through the 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, 2018b). 95% of our 15,000 estimates fall in the 0.008-0.397 range. An important caveat is that climate change-induced changes in income, poverty, or other causal drivers of child maltreatment may attenuate or exacerbate the direct effects of increases in maximum daily temperatures. Thus, the back-of-the-envelope results depicted in Figure 9 should be interpreted with caution.

6 Conclusion

While a large literature identifies ongoing risk factors for child maltreatment, such as poverty, housing instability, 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, 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. Specifically, we exploit annual variation in maximum temperatures within calendar month and US county, above and beyond any common time shocks, in order to examine the immediate effects of temperature on maltreatment of young children. We find robust evidence that hot temperatures increase the maltreatment allegation and victimization rates

[30]Estimates are very similar when we focus on the set of counties in our analysis sample in Figure A12.

for young children, with no evidence of differential substantiation during hotter periods. We also find reductions in maltreatment victimization rates at colder temperatures. However, the pattern of results comparing allegations and victimization rates suggests that at least some of that reduction is due to differential decreases in reporting at cold temperatures.

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 the victimization rate for child physical abuse. 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 medical data is mixed, with Gruenberg et al. (2019) finding an increases in abuse-related hospital admissions on hot days, but Mehta et al. (2022) finding no increases in abusive head trauma.

By contrast, our results suggest that child neglect is measurably responsive to changes in temperature. Given the definition of maltreatment outlined in section 2.1—"an act or failure to act which presents an imminent risk of serious harm," this implies that 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 alone in hot cars, unsupervised access to weapons or dangerous substances, or allowing children to play outdoors unattended in ways that could place them in danger (such as near a busy road). Inattentive parenting could result from changes in time use or from changes in adult cognitive capacity, which has been found to decline in hot weather (Almås et al., 2019). It is important to note that 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. However, our results are consistent with the recent findings of Gould et al. (2024), who do not address child maltreatment directly, but document strikingly similar patterns in emergency department admissions related to accidental injuries and poison.

The association between high temperatures and increases in child maltreatment that we document in our study adds to the body of literature documenting the potential adverse effects of climate change. In particular, increases in the frequency of hot days may lead to increases in the incidence of acute neglect and bring more families in contact with law enforcement and the child welfare system. Additional funding for child welfare services and affordable access to childcare could possibly mitigate these effects. However, traditional measures of mitigation through air conditioning do not seem to moderate our estimates.

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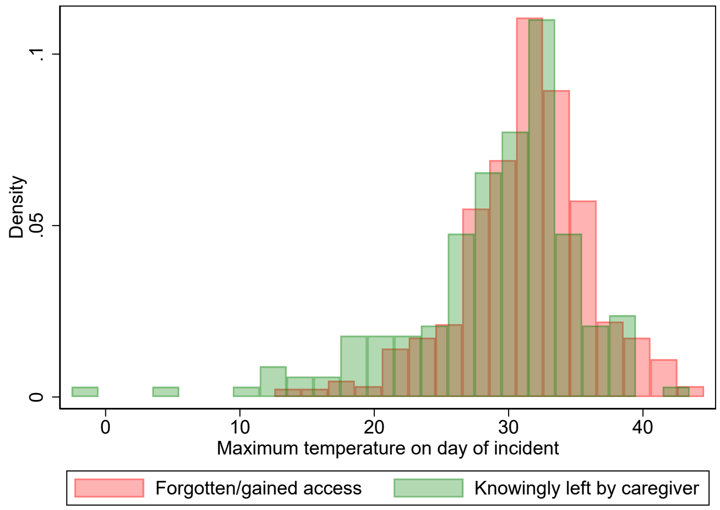
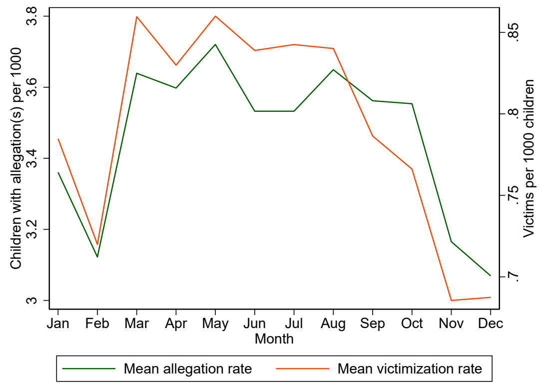
Figures and Tables

Figure 1: Heatstroke and hypothermia vehicular child deaths, 2001-2022

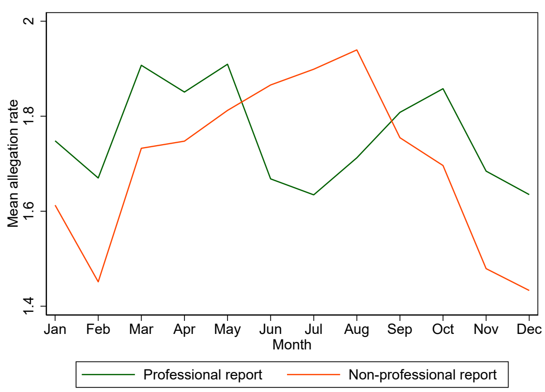


Notes: Figure shows histograms of the maximum temperature on the incident day based on the county in which the incident took place by the circumstances underlying the child death. We assign daily temperatures to counties based on a population-weighted spatial average of grid cells covering the county area. Information is collected from searches of electronic news media. Most deaths arise from heatstroke, the most serious form of hyperthermia. A small number of deaths result from hypothermia at cold temperatures. Data source: Jan Null, CCM, Department of Meteorology and Climate Science, San Jose State University, http://noheatstroke.org.

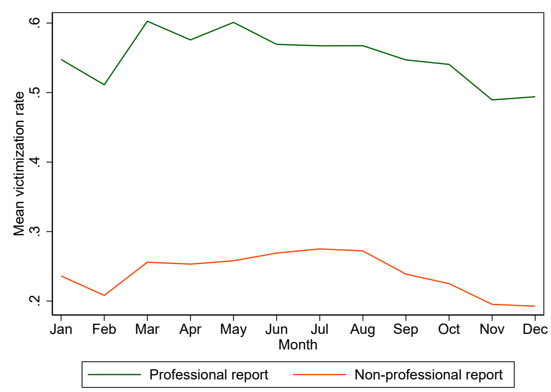
Figure 2: Seasonal Variation in Child Maltreatment Overall and by Report Source



(a) Mean allegation and victimization rates



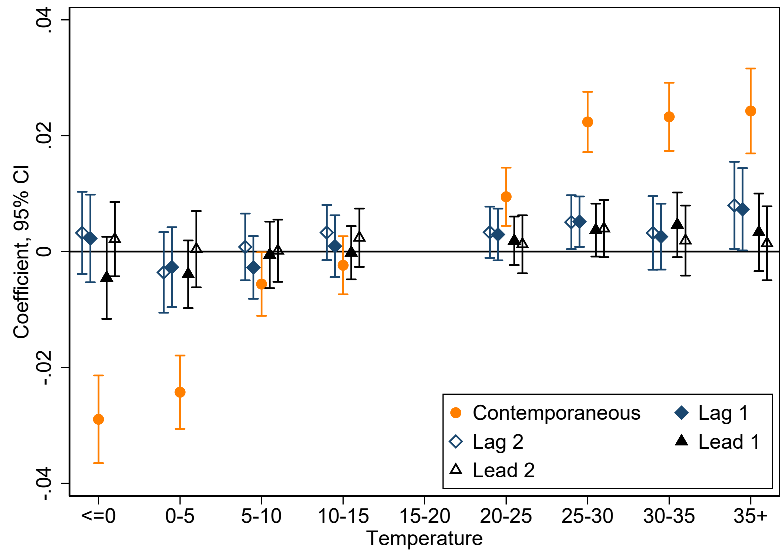
(b) Mean allegation rate by report source



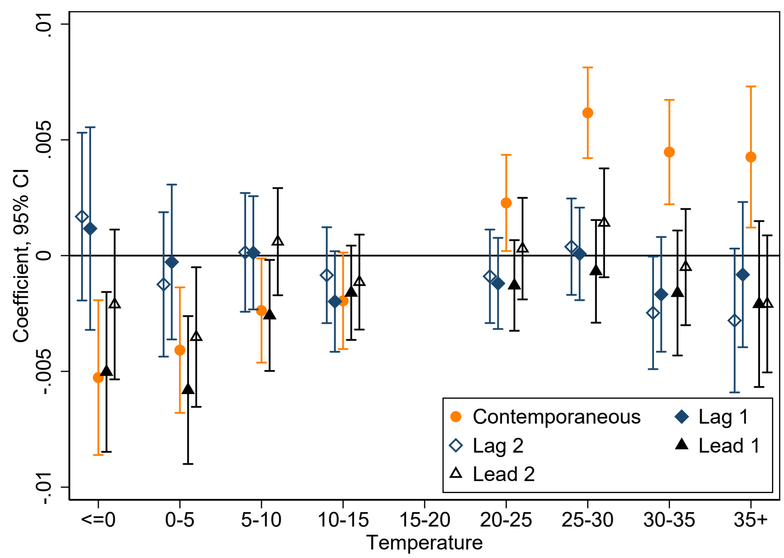
(c) Mean victimization rate by report source

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. The allegation rate measures the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the bimonthly 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 bimonthly reporting period. Panels (b) and (c) plot monthly means of the allegation and victimization rates, respectively, by report source category.

Figure 3: Relationship between Temperature and Maltreatment of Young Children



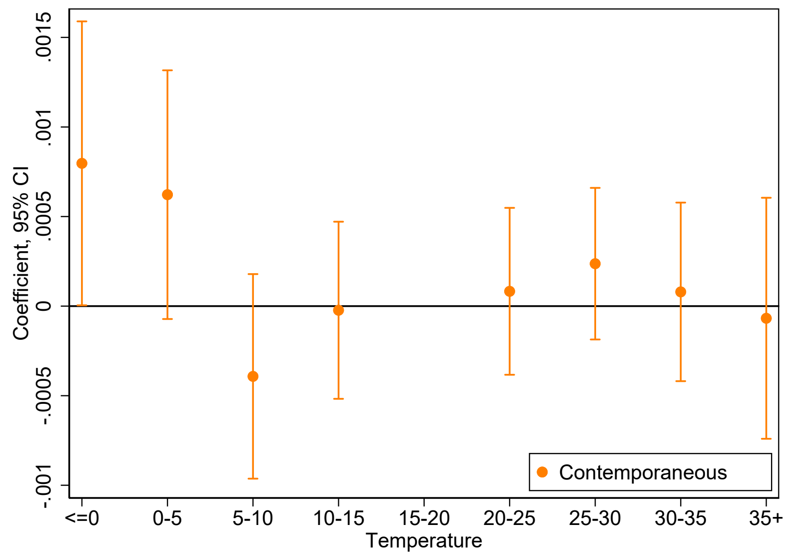
(a) Allegation rate



(b) Victimization rate

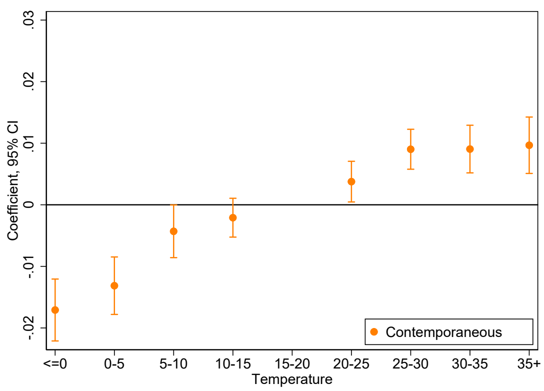
Notes: This figure plots the estimated coefficients and 95% confidence intervals on the temperature bin variables in the main specification. The estimated coefficients of interest are in orange and denoted with circles. Diamonds denote estimated coefficients on lagged temperature variables while triangles 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-bimonthly reporting 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-bimonthly reporting period. The sample mean (standard deviation) victimization rate is 0.792 (0.725).

Figure 4: Relationship between Temperature and Report Substantiation Rate

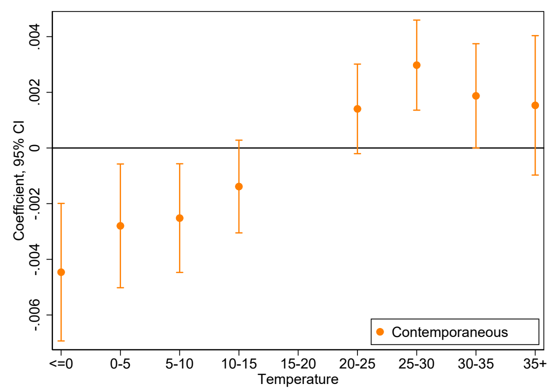


NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables in the main specification. The outcome variable is the substantiation rate, i.e. the fraction of children age 0-4 who are found to be victims of child maltreatment among those with allegation(s). The substantiation rate is the victimization rate divided by the allegation rate. The sample mean (standard deviation) substantiation rate is 0.233 (0.143).

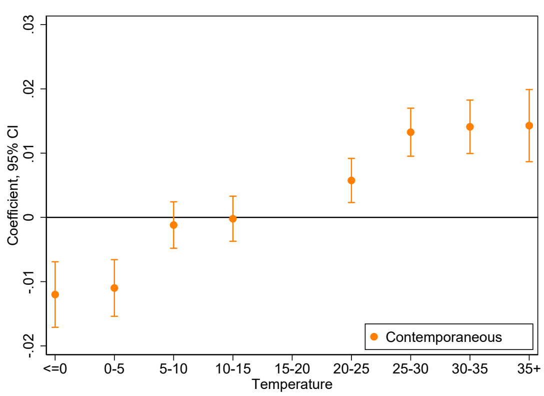
Figure 5: Relationship between Temperature and Maltreatment of Young Children by Report Source



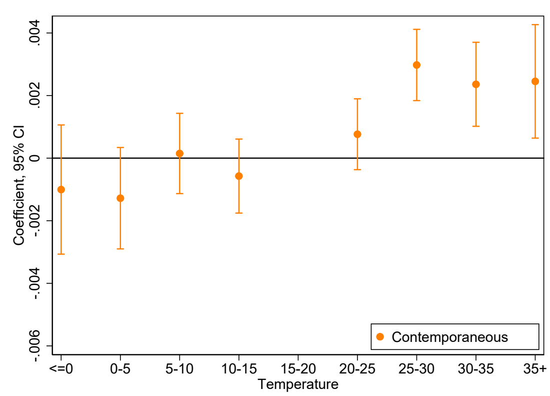
(a) Allegation rate, professional



(b) Victimization rate, professional



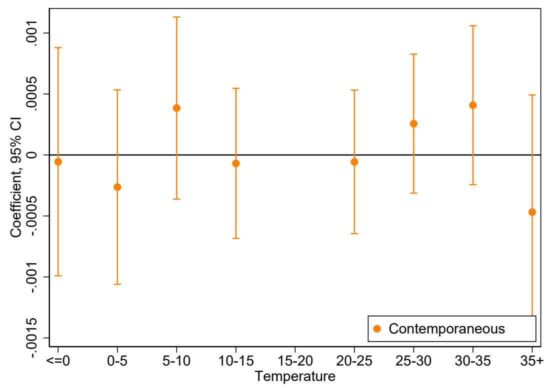
(c) Allegation rate, non-professional



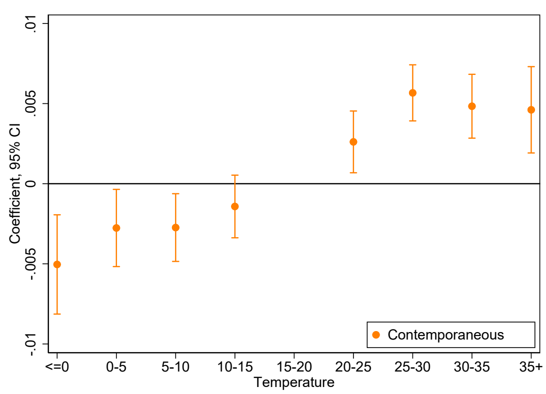
(d) Victimization rate, non-professional

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 during the bimonthly reporting 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 during the bimonthly reporting 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.

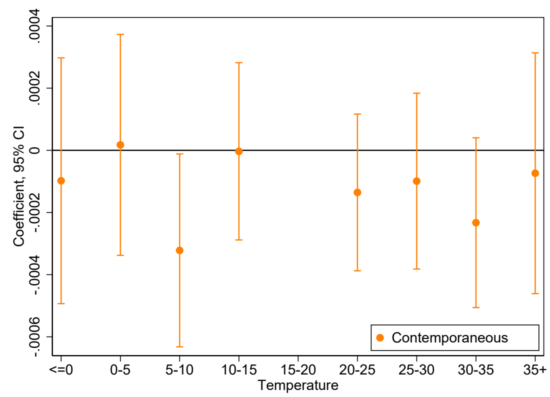
Figure 6: Relationship between Temperature and Victimization Rate of Young Children by Maltreatment Type



(a) Physical abuse



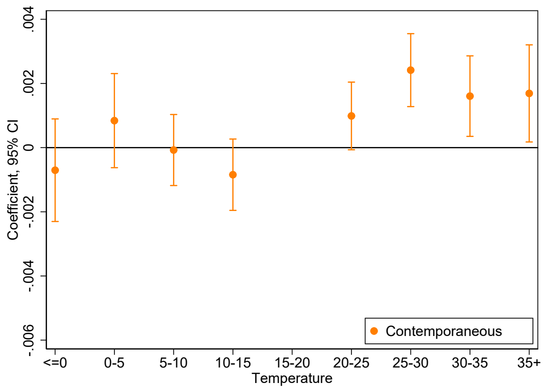
(b) Neglect



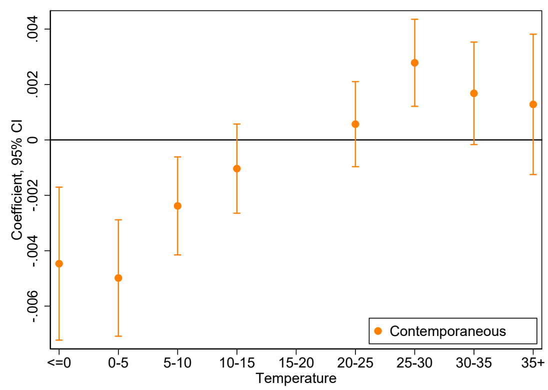
(c) Sexual abuse

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. The victimization rate is the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure 7: Relationship between Temperature and Victimization Rate of Young Children by Prior Victim Status



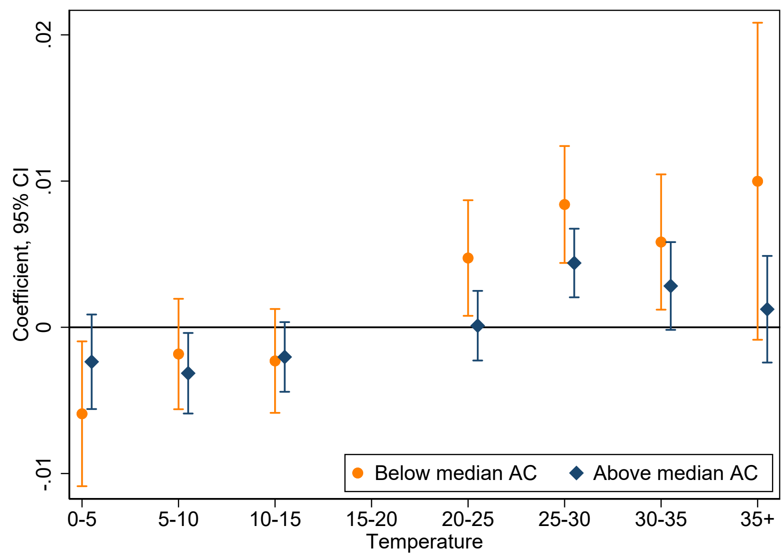
(a) Prior victim



(b) Not prior victim

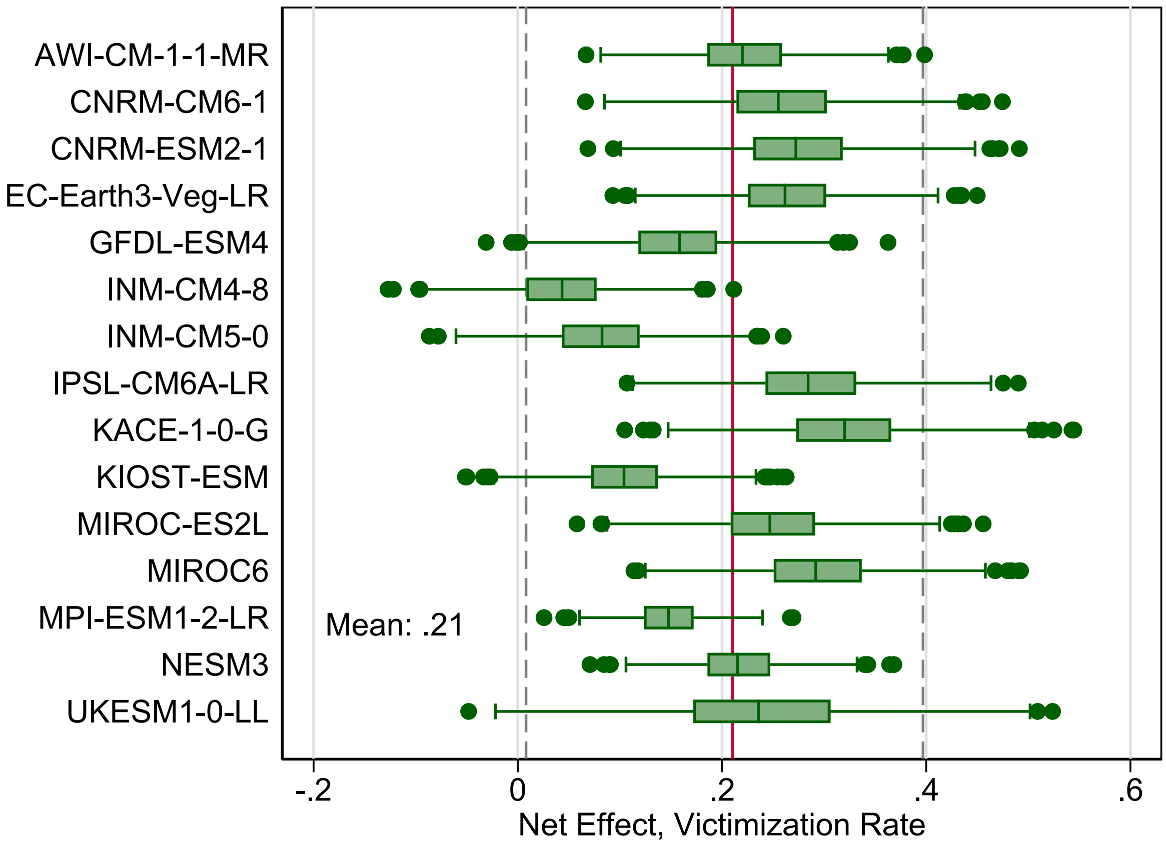
Notes: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Both panels plot results for the victimization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

Figure 8: Relationship between Temperature and Victimization Rate of Young Children by Air Conditioning Penetration



NOTES: This figure plots the estimated coefficients and 95% confidence intervals on (1) the contemporaneous temperature bin variables, and (2) sums of these estimated coefficients and those on interactions between the contemporaneous temperature bin variables and an indicator for county-level above-median air conditioning penetration in 2005. (1) is depicted as orange circles while (2) is denoted with blue diamonds. 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, the number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure 9: 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)	(8)
Panel A: Allegation rate								
35+ Celsius	0.0243***	0.0208***	0.0180***	0.0179***	0.0224***	0.0244***	0.0174***	0.0162***
	(0.00374)	(0.00333)	(0.00291)	(0.00292)	(0.00347)	(0.00403)	(0.00248)	(0.00301)
	[0.00688]							
Panel B: Victimization rate								
35+ Celsius	0.00426**	0.00419**	0.00288*	0.00290*	0.00377*	0.00330*	0.00322***	0.00168
	(0.00156)	(0.00146)	(0.00135)	(0.00136)	(0.00148)	(0.00158)	(0.000818)	(0.00128)
	[0.00133]							
County-year & precipitation controls	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
County-bimonthly period	Yes	No	No	No	No	Yes	Yes	Yes
County-month fixed effects	No	Yes	No	No	Yes	No	No	No
State-year fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Reporting period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	No	Yes	No	No	No	No	No	No
County fixed effects	No	No	Yes	Yes	No	No	No	No
County X linear year	No	No	No	Yes	No	No	No	No
Temperature lags	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Temperature leads	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
County population weights	No	No	No	No	No	No	Yes	No
Alternative sample	No	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. 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. Column (8) uses an alternative sample of larger counties. Standard errors in parentheses are clustered on county. Standard errors in brackets are clustered on state. Main sample includes 114,312 observations, which represent 433 unique counties for 264 bimonthly periods. Alternative sample includes 93,456 observations, which represent 354 unique counties for 264 bimonthly periods.

A Online Appendix

A.1 Construction of panel dataset

In this Appendix we describe the process by which we form a balanced county-by-bimonthly period using the NCANDS Child Files for 2006 to 2018. 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.

We first identify the 435 counties in 44 states that are unmasked in all 13 Child Files from 2006 to 2018. We then remove cases from the counties that are not continuously unmasked in the Child Files between 2006 and 2018, cases from Puerto Rico (due to data quality concerns), cases for which county of report is masked or missing including child fatalities, and cases with a report year earlier than 2006 or later than 2016. The next step involves identifying cases that appear in multiple Child Files. For these cases, we follow the recommendation in the NCANDS User's Guide to keep only the instance in the most recent fiscal year. Finally, we remove cases in which the child's age is above 4 or missing.[31].

About 6.5% of cases have missing values for report source and less than a half percent of cases have missing values for maltreatment type. 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.

We construct maltreatment outcomes at the child-level (as opposed to the case- or report-level). To do so we collapse the data to create a count of the number of unique children between the ages of zero and four (e.g., with at least one allegation, with at least one substantiated allegation, etc.) in the county and bimonthly period. We then scale by annual

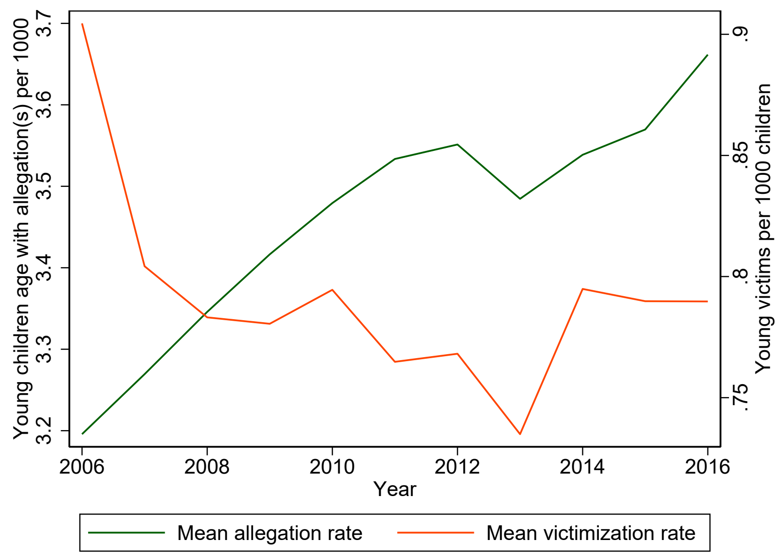
[31] Fewer than one percent of child observations have missing values for age

child population in the county measured in thousands from SEER. The resulting balanced county-by-bimonthly 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.

A.2 Additional figures and tables

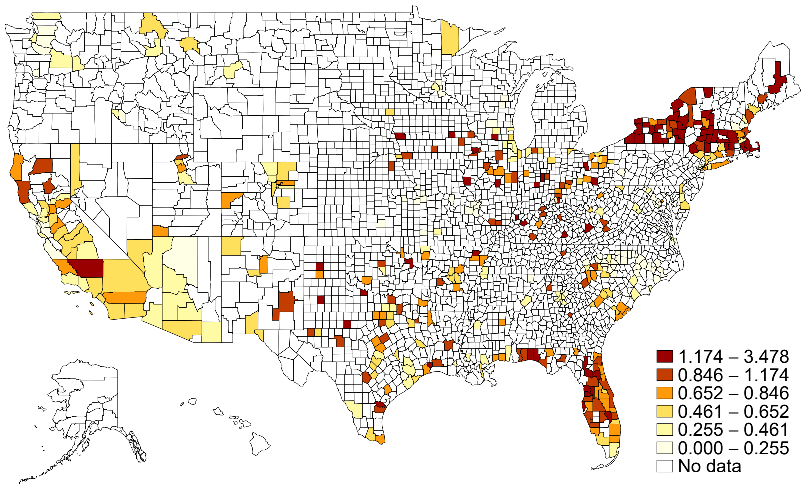
Figure A1: Temporal Variation in Maltreatment of Young Children



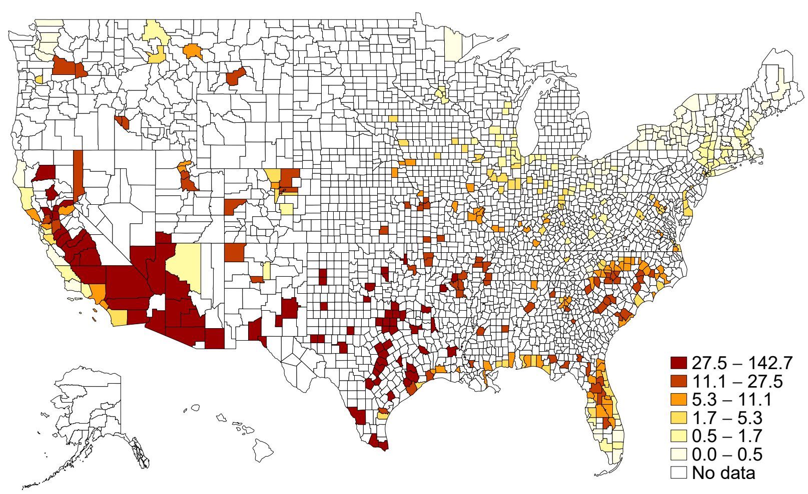
(a) Annual variation

NOTES: This figure 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 in the county-bimonthly reporting period. The victimization rate measures the number of children per 1,000 with at least one substantiated maltreatment allegation in the county-bimonthly reporting period.

Figure A2: Spatial Variation in Child Maltreatment (Age 0-4) and Temperature



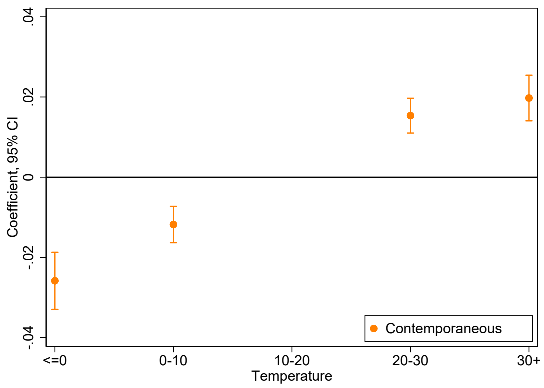
(a) Median victimization rate



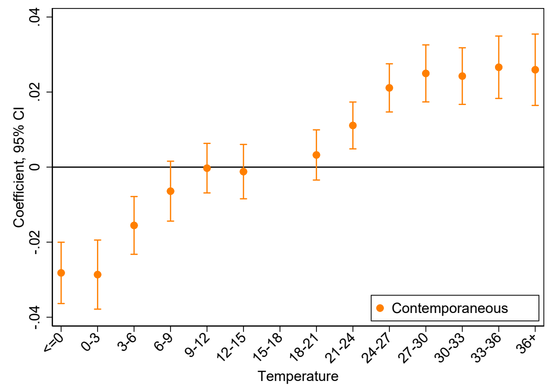
(b) Average number of days with maximum temperature of 35+°C

Notes: This figure depicts spatial variation in victimization rates and temperatures. Panel (a) plots the median victimization rate for young children in the bimonthly period for 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-bimonthly reporting period. Panel (b) shows the average annual number of days in each county with maximum temperatures above 35 °C over the sample period, 2006-2016.

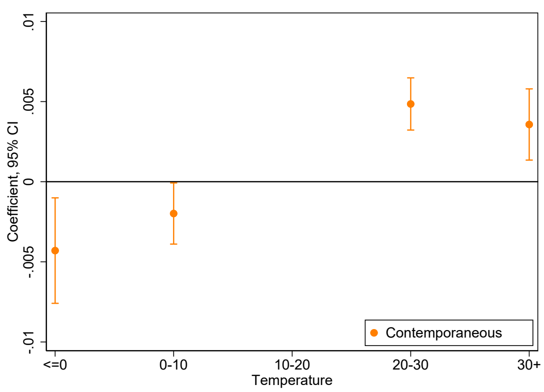
Figure A3: Relationship between Temperature and Maltreatment of Young Children, Alternative Temperature Bins



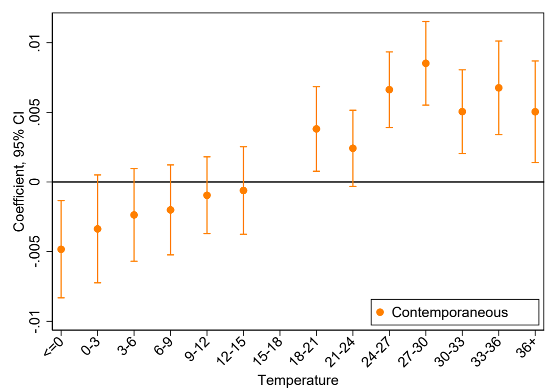
(a) Allegation rate: 10-degree bins



(b) Allegation rate: 3-degree bins



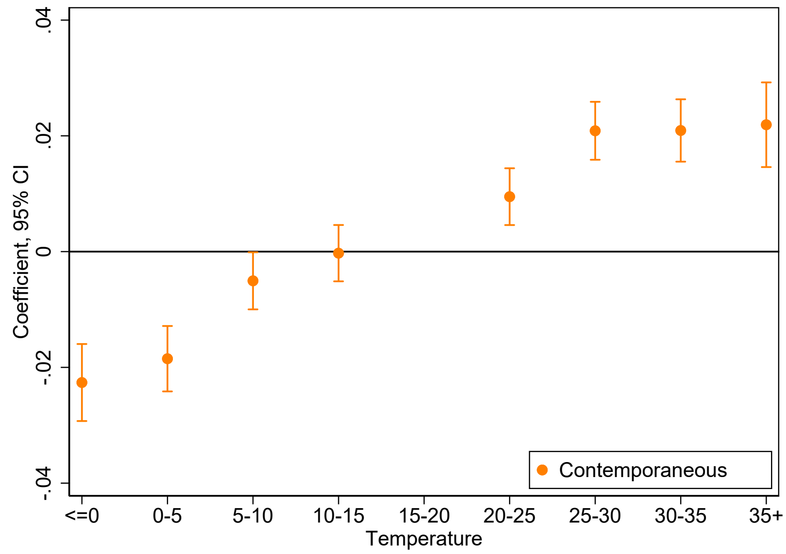
(c) Victimization rate: 10-degree bins



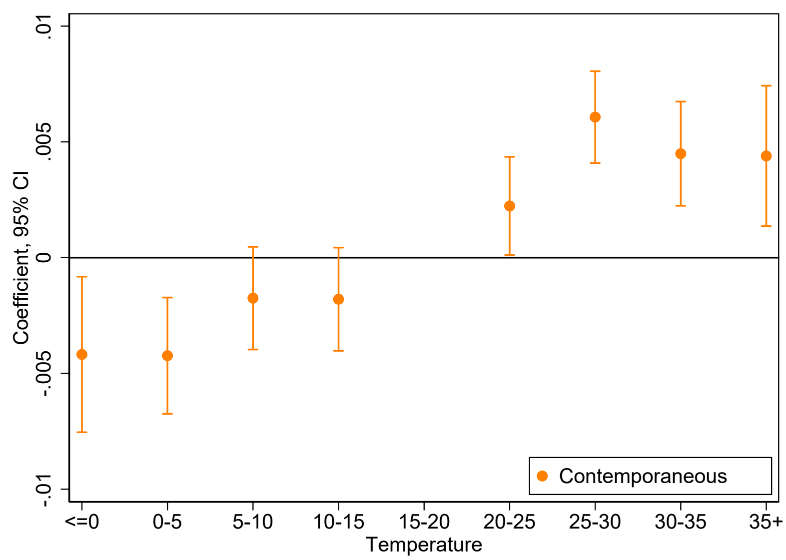
(d) Victimization rate: 3-degree bins

Notes: This figure plots the estimated coefficients and 95% confidence intervals on the temperature bin variables defined over 10°C (Panels (a) and (c)) and over 3°C (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-bimonthly reporting 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-bimonthly reporting period.

Figure A4: Relationship between Temperature and Maltreatment of Young Children, Alternative Assignment of Weather Variables



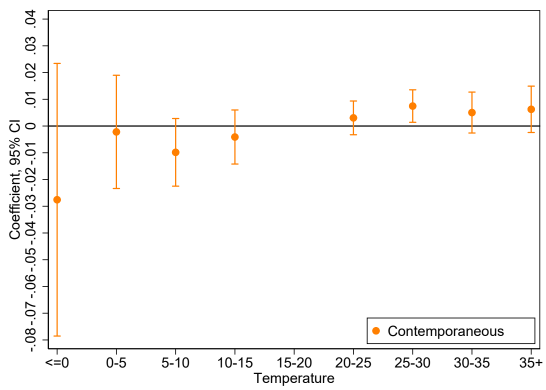
(a) Allegation rate



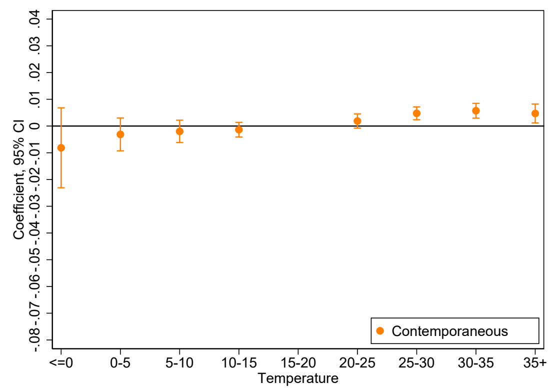
(b) Victimization rate

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 bimonthly reporting 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 bimonthly reporting 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.

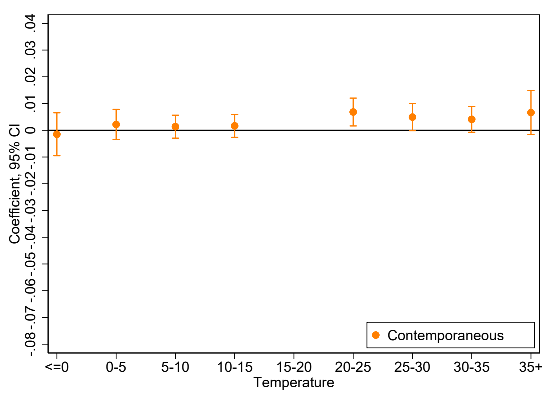
Figure A5: Relationship between Temperature and Victimization Rate for Young Children by Climate Zone



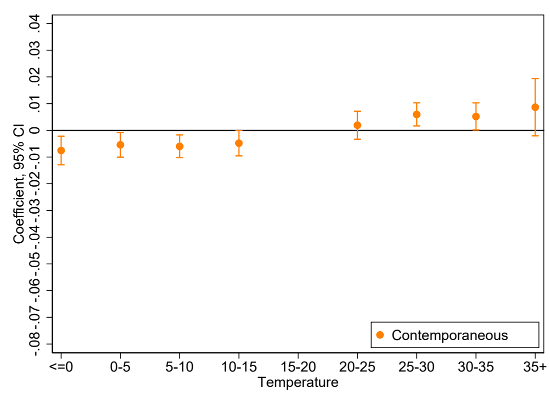
(a) Zones 1-2



(b) Zone 3



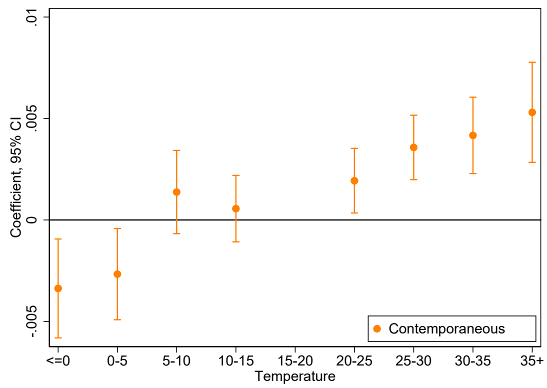
(c) Zone 4



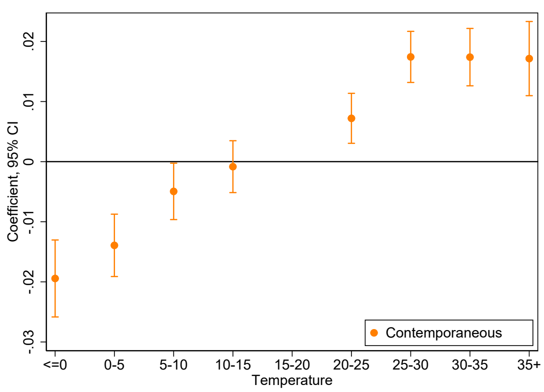
(d) Zones 5-7

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-bimonthly reporting period.

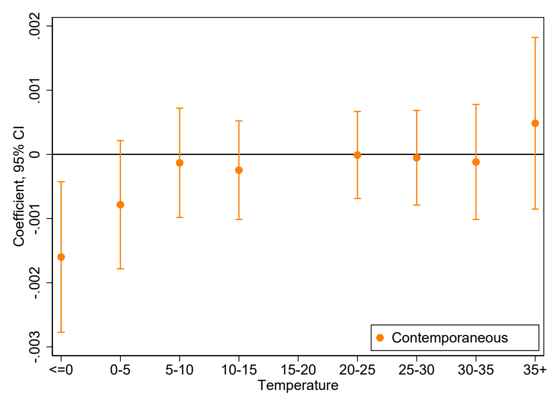
Figure A6: Relationship between Temperature and Allegation Rate for Young Children by Maltreatment Type



(a) Physical abuse



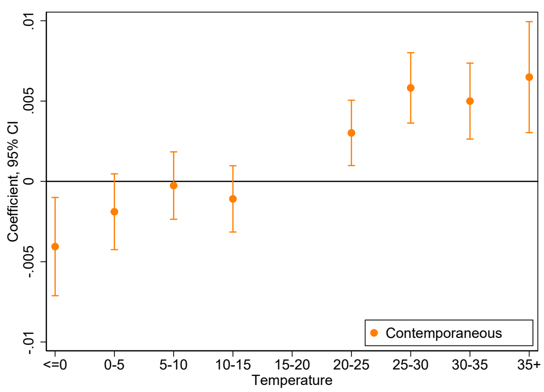
(b) Neglect



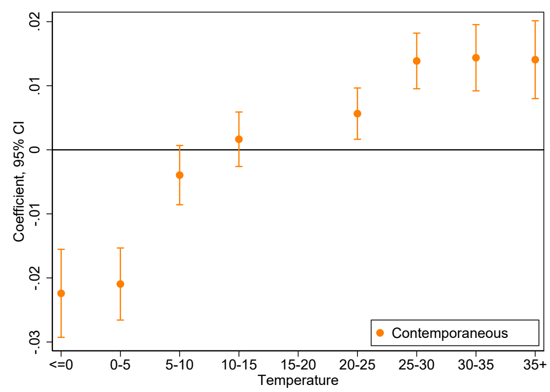
(c) Sexual abuse

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. The allegation rate is the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the county-bimonthly reporting period.

Figure A7: Relationship between Temperature and Allegation Rate for Young Children by Prior Victim Status



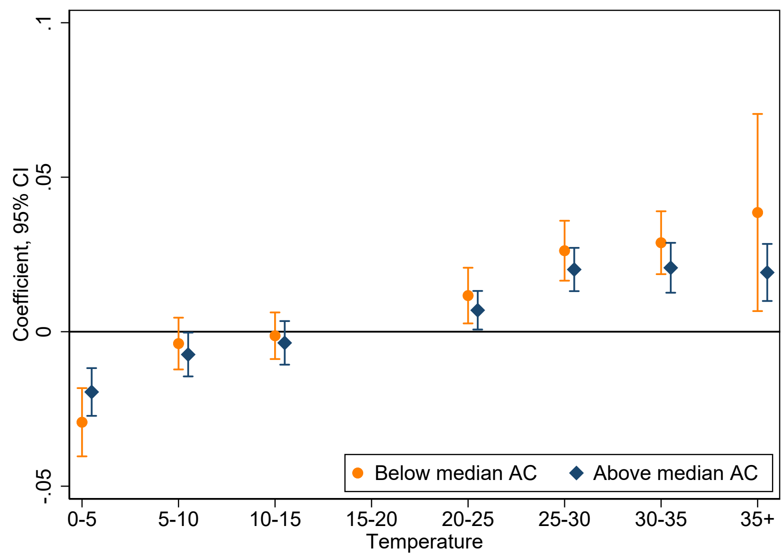
(a) Prior victim



(b) Not prior victim

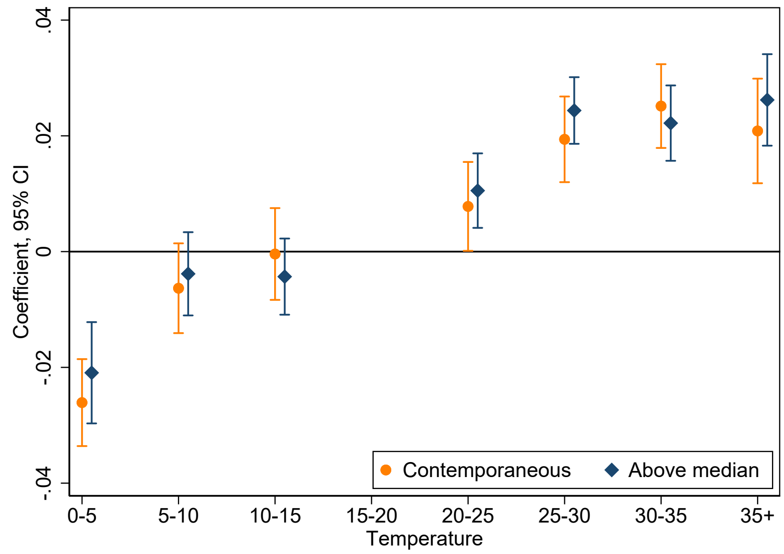
NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Both panels plot results for the allegation rate, the number of children age 0-4 per 1,000 with at least one allegation during the county-bimonthly reporting period. Panel (a) shows results for children who are known to be prior victims of maltreatment while while panel (b) depicts results for children who are not known to be prior maltreatment victims.

Figure A8: Relationship between Temperature and Allegation Rate for Young Children by Air Conditioning Penetration

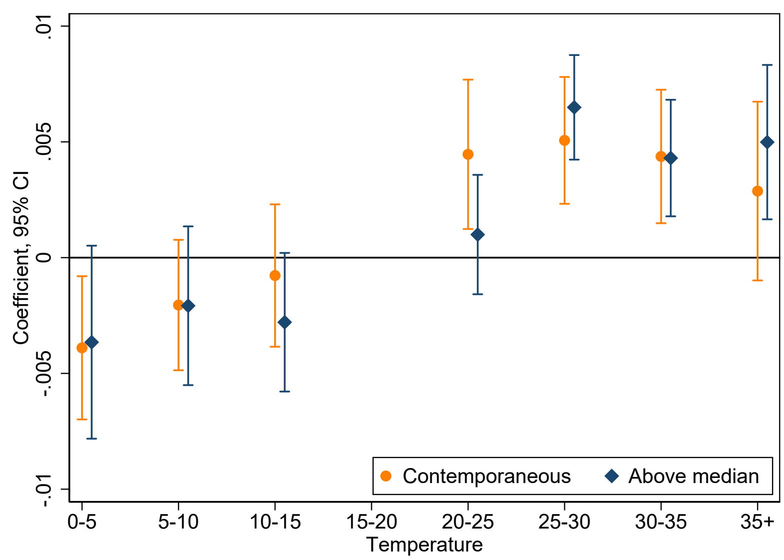


NOTES: This figure plots the estimated coefficients and 95% confidence intervals on (1) the contemporaneous temperature bin variables, and (2) sums of these estimated coefficients and those on interactions between the contemporaneous temperature bin variables and an indicator for county-level above-median air conditioning penetration in 2005. (1) is depicted as orange circles while (2) is denoted with blue diamonds. 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 allegation rate, the number of children age 0-4 per 1,000 with at least one maltreatment allegation during the bimonthly reporting period.

Figure A9: Relationship between Temperature and Maltreatment of Young Children by Energy Prices



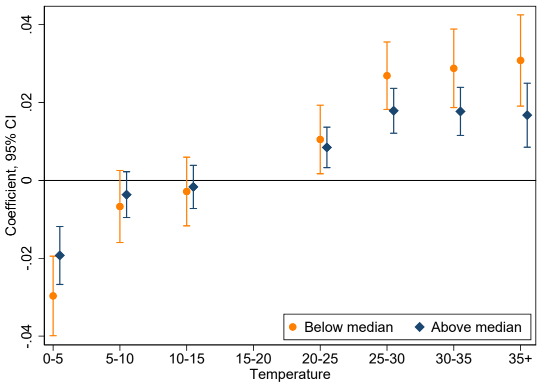
(a) Allegation rate



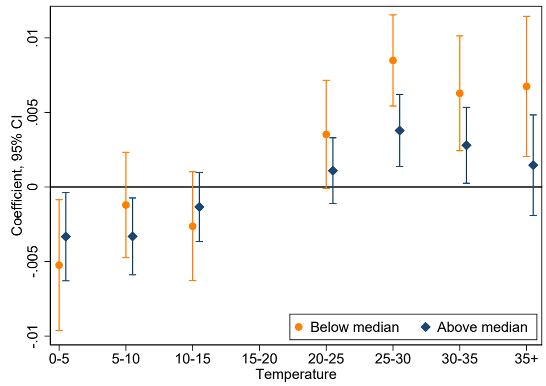
(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on (1) the contemporaneous temperature bin variables, and (2) sums of these estimated coefficients and those on interactions between the contemporaneous temperature bin variables and an indicator for above-median energy prices in a state-month. We obtained monthly residential energy prices at the state level from the US Energy Information Administration. (1) is depicted as orange circles while (2) is denoted with blue diamonds. 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 bimonthly reporting 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 bimonthly reporting period.

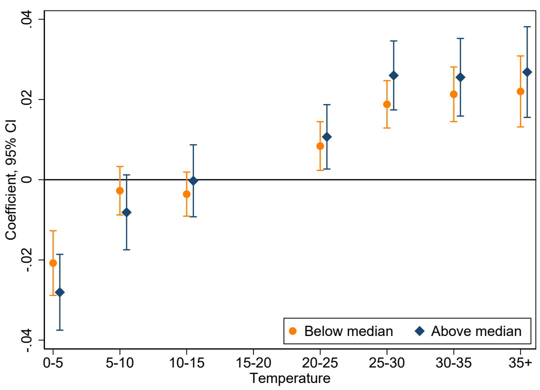
Figure A10: Relationship between Temperature and Maltreatment of Young Children: Heterogeneous Effects



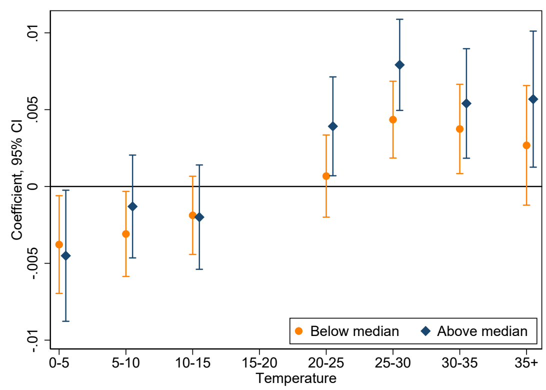
(a) Median HH income, Allegation rate



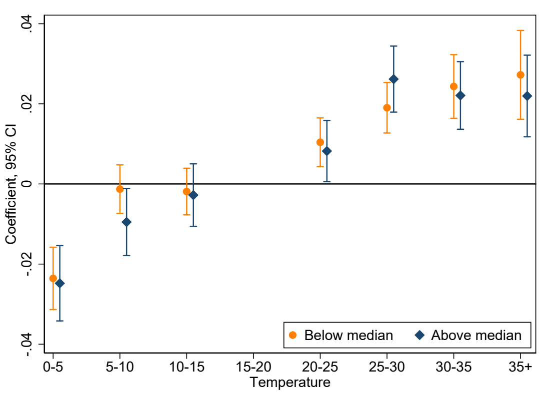
(b) Median HH income, Victimization rate



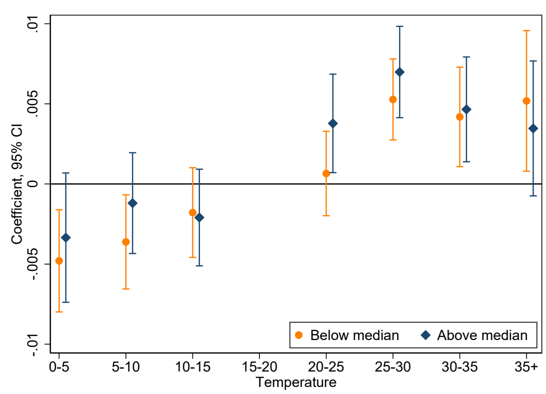
(c) % children in poverty, Allegation rate



(d) % children in poverty, Victimization rate



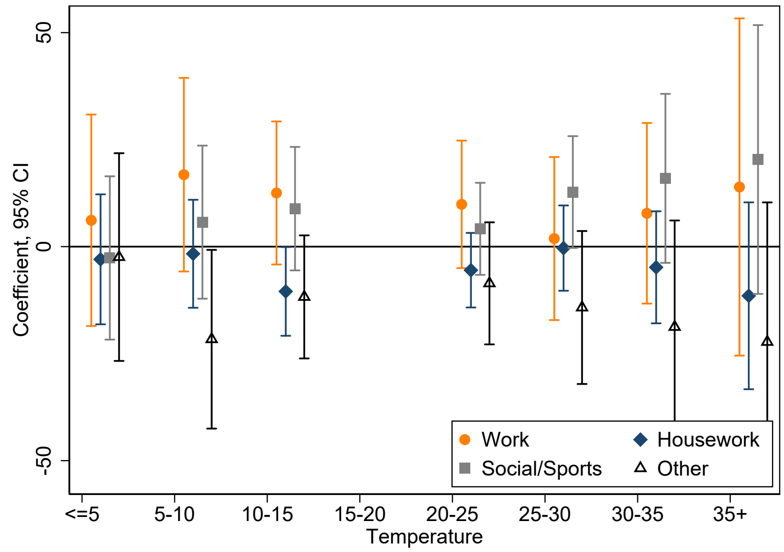
(e) Unemployment rate, Allegation rate



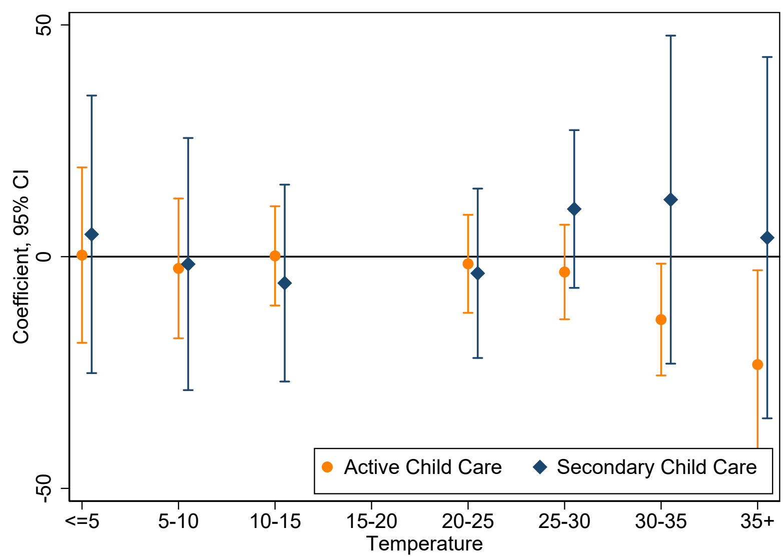
(f) Unemployment rate, Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on on (1) the contemporaneous temperature bin variables, and (2) sums of these estimated coefficients and those on interactions between the contemporaneous temperature bin variables and an indicator for county-level above-median values of three control variables in 2006: median household income, share of children in poverty, and unemployment rate. (1) is depicted as orange circles while (2) is denoted with blue diamonds. Temperature leads and lags are included. Controls and fixed effects are as described in the main specification. Panels (a), (c), and (e) show the estimated relationship between temperature and the allegation rate, while Panels (b), (d), and (f) focus on the victimization rate.

Figure A11: Relationship between Temperature and Parental Time Use



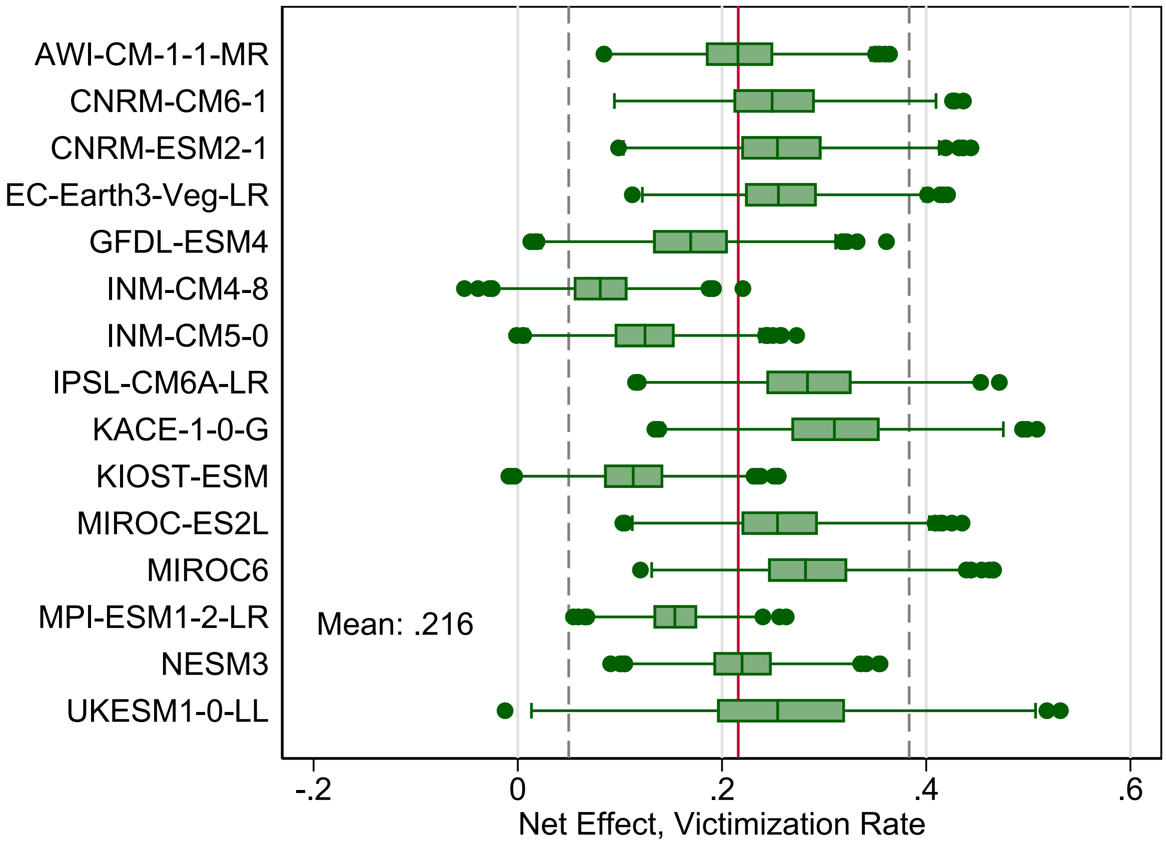
(a) General Activities



(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—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 A12: Average Predicted Change in Victimization Rate for Young Children in 2081-2100 Due to Climate Change, Sample Counties



Notes: This figure plots the estimated change in the victimization rate of children aged 0-4 attributable to climate change in our sample counties, 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 (0.05 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, educational source	0.284
	(0.356)
Allegation rate, medical source	0.452
	(0.417)
Allegation rate, social services source	0.374
	(0.444)
Allegation rate, law enforcement source	0.653
	(0.632)
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, educational source	0.038
	(0.098)
Victimization rate, medical source	0.132
	(0.179)
Victimization rate, social services source	0.117
	(0.205)
Victimization rate, law enforcement source	0.266
	(0.320)
Victimization rate, prior victim	0.209
	(0.328)
Victimization rate, not prior victim	0.536
	(0.528)

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 mean and standard deviation for the substantiation rate are 0.233 and 0.143, respectively. 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.