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. Additional analysis identifies neglect as the temperature-sensitive maltreatment type, and we do not find 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;
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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 (U.S. Department of Health and Human Services, Administration for Children and Families, 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 identifies several channels through which extreme temperatures might affect actual and/or observed child maltreatment. First, extreme 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 temperatures may affect time use for children and adults (Graff Zivin and Neidell, 2014). Changes in time use may result in adults and children spending more time together in confined spaces, perhaps leading to increased parental stress; or may change the likelihood of maltreatment being

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

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, for some parental actions, hot temperatures can create an environment in which a child is at increased risk of harm compared to more moderate temperatures (e.g., leaving a child alone at home or in a car).

This paper sheds light on the effect of rising temperatures on child welfare by estimating the impacts of extreme 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). Our data cover the period from 2006 to 2016. We focus on the average daily number of children per 1,000 with alleged and substantiated maltreatment in a county and bimonthly reporting period, as well as by a variety of case characteristics.

To measure temperature variation, we use modeled gridded daily weather data from the PRISM Climate Group at Oregon State University. We focus on the maximum of the daily maximum temperature over the bimonthly period. Our empirical strategy exploits variation in temperatures within calendar month and county to control for county-specific seasonal patterns. We also include state-year fixed effects that absorb, for example, policy variation over time at the state level, as well as reporting period fixed effects that absorb national idiosyncratic shocks.

We find increases in alleged and substantiated child maltreatment among young children during hot periods (with maximum temperatures greater than 25° Celsius or 77° Fahrenheit). In particular, we estimate that in reporting periods when the maximum temperature reaches 35°C, the maltreatment allegation rate increases by 3.87% relative to the mean, while the victimization rate increases by 5.16%. We provide evidence suggesting that our results are not driven by changes in reporting. Additional analysis identifies acute neglect, particularly involving law enforcement reporting, as the temperature-sensitive maltreatment type. Moreover, we find an increase in "first incidents", that is alleged and substantiated maltreatment among children not previously involved in the child welfare system. Combining predictions from 25 global climate models and 1,000 bootstrap replications, we estimate that over the period 2061-2080, climate change will lead to an annual average increase in the number of young children with a substantiated maltreatment case per county-day of 13% over the current mean, with 95% of our 25,000 estimates being positive.

Our work identifies a novel channel through which climate change will adversely impact child welfare—by increasing the probability of extreme temperatures and, as a result, child

maltreatment. Importantly, we find that effects of temperature increases are largest for counties with more temperate "normal" climates, but we do not find 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 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, among other activities. The Act has been amended and reauthorized several times.[2] 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 (U.S. Department of Health and Human Services, Administration for Children and Families, 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

[2]See US Department of Health and Human Services, Children's Bureau (2019a).

these categories vary across states.[3] Among types of child maltreatment, neglect is the most complex and most common, accounting for over three-fourths of confirmed cases of child maltreatment in the US in 2020 (U.S. Department of Health and Human Services, Administration for Children and Families, 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 (US Department of Health and Human Services, Children's Bureau, 2018). 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., 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 (e.g., leaving a young child alone in a car). 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 (US Department of Health and Human Services, Children's Bureau, 2019b).

The determination that a child is a victim of maltreatment begins with a referral of suspected child maltreatment to a CPS agency. 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 (U.S. Department of Health and Human Services, Administration for Children and Families, Children's Bureau, 2019). Most frequently these include social workers, healthcare professionals, law enforcement officers, and educational and childcare personnel. Once received, CPS evaluates whether or not the referral meets agency criteria for an investigation or alternative response (e.g., provision of services). If so, then the referral is "screened in."[4] 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 (U.S. Department of Health and Human Services, Administration for Children and Families, Children's Bureau, 2021). After investigation by the CPS agency, the

[3] U.S. Department of Health and Human Services, Administration for Children and Families, Children's Bureau (2022) provides more detailed information on variation in civil definitions of child maltreatment across states.

[4] According to U.S. Department of Health and Human Services, Administration for Children and Families, 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.

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. As described in more detail in the next section, our analysis relies on administrative data from state CPS agencies. Given the extent of underreporting and the failure to substantiate valid allegations (Waldfogel, 1998), maltreatment measures based on administrative data, like those we construct, likely underestimate the true amount of child maltreatment (Lindo and Schaller, 2014). Bald et al. (2022) emphasize that prevalence measures based on administrative data only reflect child maltreatment reported to CPS agencies.[5] 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 in particular 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).[6]

2.2 Potential mechanisms linking temperature and child maltreatment

Potential mechanisms linking ambient temperature and measured child maltreatment fall into three categories: (1) effects of temperature on the 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 recorded in our data. In considering potential channels, we can

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

[6] 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.

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, including adult cognitive capacity, childcare decisions, and environmental risk factors like outdoor play and hot cars.[7]

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). 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

[7]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.

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). Changes in time use may also result in changes in exposures 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). Meanwhile during winter weather, people may not interact as often and appointments with potential reporters (e.g., doctors, CPS workers) may be delayed.

The extent to which these various channels operate depends on a range of factors, one of which is child age. By focusing on young children, we hope to distinguish a temperature-child maltreatment relationship from merely a temperature-reporting of child maltreatment relationship. Our focus on young children is motivated by a number of factors. 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). 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 and active.[8] Thus, identifying maltreatment as the likely source of some physical injuries for older children may be more challenging compared to younger children. In the next section, we explore differences in the patterns of maltreatment for young children and for school aged children in the raw data; this exercise further supports our focus on the former for our empirical analysis.

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 the necessary weather

[8]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.).

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.[9]

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, 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 the 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 1st and 15th days of the month or between the 16th and the end of month, during which the report of child maltreatment was made. The exact report and incident dates are masked.[10] Given these features of the data, we form a balanced county-by-bimonthly period panel representing 424 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

[9]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.

[10]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.

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.

We form two primary maltreatment outcomes, the allegation rate and the victimization rate, both measured at the county-by-bimonthly period level. Because the number of days is not constant across bimonthly periods, we construct maltreatment measures that reflect daily averages within the bimonthly period. The allegation rate is the number of children per 1,000 with at least one screened-in child maltreatment report on an average day in the county-bimonthly period. The victimization rate reflects the number of children per 1,000 considered to be victims of child maltreatment on an average day in the county-bimonthly 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.[11] Changes over our sample period in the allegation and victimization rates for all children ages 0 to 17 are presented in Figure A1a, which depicts patterns similar to those 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 A1b). Both maltreatment measures are generally lower in November and December and the summer months of June through August. Importantly for our analysis, the raw data reveal stark differences in the seasonal pattern of allegation and victimization rates for young children (age 0 to 4) and school-aged children (age 5 to 17) (Figure 1). Figure 1b suggests that the drop in maltreatment during the summer months visible in Figure A1b is driven by school-aged children; maltreatment among young children is not substantially lower in summer months (Figure 1a). Furthermore, the seasonal patterns of child maltreatment based on reports from professional sources and non-professional sources differ markedly between young (Figure 1c) and school-aged children (Figure 1d).[12] These differences may result from more variation in exposure to mandatory reporters among school-aged children across the year (i.e., less exposure to teachers during the summer when school is out) and/or other sources of variation (e.g., time use). Given this observation and the fact that maltreatment is most prevalent among the youngest children, our empirical analysis presented in the next section focuses on children ages 0 to 4.

Figure A2 shows spatial variation across sample counties in the median victimization rate

[11] Table A1 reports means and standard deviations for all outcome measures.

[12] See Appendix A for details on how we classify reporters as professional and non-professional.

for young children between 2006 and 2016. Among sample counties, victimization rates are highest in counties in New York and Massachusetts. According to U.S. Department of Health and Human Services, Administration for Children and Families, 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 maximum and minimum daily temperature, as well as total daily precipitation, using a model that accounts for factors that influence local climate (e.g., elevation, wind direction). For each county, we assign the weather measures associated with the grid cell that contains the county centroid.[14] We construct weather variables at the county-bimonthly level. Following related work (e.g., Barreca and Schaller (2020), Park et al. (2020)), we focus on daily maximum temperatures. Specifically, we use the maximum of the daily maximum temperatures over the bimonthly period for each county. We construct indicators that equal one if this 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.

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

$$
\begin{aligned}
Y_{it} = & \sum_{j} \beta^{j} \text{MaxTemp}_{\text{it}} \text{ in Bin}_{j} \\
& + \sum_{j} \sum_{l \in \{1,2\}} \gamma_{l}^{j} \text{MaxTemp}_{\text{it}} \text{ in Lagged/Lead Period l in Bin}_{j} \\
& + \pi X_{it} + \alpha Z_{iy(t)} + \eta_{im(t)} + \phi_{s(i)y(t)} + \delta_{t} + \varepsilon_{it}
\end{aligned}
$$

where Y_{it} denotes the child maltreatment outcome in county i and bimonthly reporting period t. The $\text{MaxTemp}_{\text{it}}$ in Bin_{j} is an indicator variable that equals one if the maximum of the daily maximum temperatures in county i during reporting period t lies within 5-degree Celsius bin j and zero otherwise. The model also includes two reporting period lags and leads of the temperature indicators, 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. $\alpha Z_{iy(t)}$ denotes a set of county-by-year controls. We include county-month fixed effects, $\eta_{im(t)}$, to control for county-specific seasonality; state-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 2 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 2a shows results for the allegation rate while panel 2b 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, with both outcome measures, the pattern of results suggests that contemporaneous exposure to hot temperatures is associated with more child maltreatment.

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 higher levels of child poverty

and lower median household income. A higher share Black is associated with increases in the allegation rate but not the victimization rate. 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.[15] Higher contemporaneous precipitation is associated with lower allegation and victimization rates; a one standard deviation in precipitation is associated with about a 0.01 standard deviation decrease in the allegation and victimization rates. 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 measure (i.e., the rightmost circles in panels (a) and (b) of Figure 2). 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.[16] For the allegation rate model in Panel A, the estimated coefficient represents the increase in children age 0 to 4 with allegation(s) per 1,000 on an average day in the bimonthly reporting period associated with the highest daily maximum temperature being at or above 35°C compared to more moderate temperatures (i.e., 15 to 20°C). Evaluated at the mean allegation rate of 0.208 children per 1,000, this represents a 3.87% increase. For the victimization rate in Panel B, the estimated coefficient is associated with a 5.16% increase when evaluated at the mean of 0.0521 children per 1,000. If all counties in our sample experienced an increase in the maximum of the maximum daily temperatures from the reference 15-20°C to above 35°C in one bimonthly reporting period, then this would translate into about 48 more kids age 0 to 4 per 1,000 with maltreatment allegation(s) and about 16 more victims per 1,000 among sample counties in that single bimonthly reporting period.

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 3140 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

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

[16] 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.

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. Given the inclusion criteria, the alternative sample excludes small counties that show up in the NCANDS data, and therefore in our main sample, merely because they have a large amount of child maltreatment.[17] 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. Results for the victimization rate are noisier using this specification, but the estimated coefficients are still positive at high temperatures, 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, rather than estimating the effect of different temperature *levels*, we explore the effect of *deviations* from "normal" temperatures in a county-bimonthly reporting period. We create a variable that measures, for each county-period, the "normal" maximum of the daily maximums in the county-bimonthly reporting period by averaging across years in our sample period. Then, for each county-period we compute the deviation (difference) between the actual maximum of the daily maximum temperatures during the reporting period and this "normal" maximum temperature measure. This deviation measure captures the fact that a maximum daily temperature of, for example, 30°C in the first half of June might be unseasonally warm in a county where usually high temperatures reach only 27°C in that period, but might be close to normal in other counties. We then interact this deviation with temperature bin variables based on the "normal" temperature measure for each county-period. Figure A4 reports results where the estimated coefficients reflect the change in maltreatment associated with a one degree increase in the deviation from the normal "temperature" for county-periods whose "normal" maximum temperatures fall in each bin, relative to a similar increase for county-periods whose "normal" maximum temperature falls in the 15-20°C bin. This exercise shows that the effect of a 1°C increase in maximum daily temperature in the reporting period has larger effects in more temperate county-periods, that is county-periods where the average maximum temperature is 20-30°C during our sample period. The estimated coefficients on higher temperature bin variables are consistent with some habituation

[17] These small 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.

to hotter-than-normal temperatures in counties that are typically hot.

Third, we replace our binary temperature bin variables with a set of comparably defined variables that indicate the number of days in the reporting period in which the maximum daily temperature falls in the respective ranges (Figure A5). Although interpretation is complicated by the fact that the number of days per bimonthly reporting period varies, the pattern of results is similar to our main results. Fourth, instead of relying on the location of the county centroid as we do for our main results, we assign weather variables to counties using the whole county surface. Specifically, for each county we average weather variables across grid cells that intersect the county polygon by weighing observations by the fraction of county surface they cover. Figure A6 shows that using temperature bins and precipitation controls constructed from these averages does not affect our estimates in a meaningful way. As a final exercise, we use a different data source for temperature: remotely sensed daily daytime land surface temperature using the MODIS Aquae instrument whose daytime overpass happens at approximately 1:30pm, thus capturing maximum daily temperatures well. Figure A7 depicts results, which are similar to our main results.

4.1 Evidence on mechanisms

4.1.1 From child and case characteristics

We investigate the mechanisms driving this estimated increase in *measured* maltreatment during hot periods. First, hotter temperatures might change reporting rates, selection into reporting, or the ability of CPS to conduct thorough investigations. Second, hotter temperatures might increase underlying maltreatment rates through physiological changes affecting cognition, behavior, and mood of children and caregivers. Third, hotter temperatures might exacerbate maltreatment patterns already known to CPS, causing repeat cases among children already exposed to maltreatment (intensive margin), or might cause one-off incidents that bring new children into the CPS system (extensive margin).

To assess whether hotter temperatures affect reporting, we first 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 allegation(s). 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. For example, hot temperatures might affect the temperament of likely mandatory reporters, causing them to lower their bar for reporting. Alternatively hot temperatures may change access to potential reporters: for instance, a neighbor might hear noises through open windows or notice bruises on children

playing outside while wearing little clothing. In these two examples, we would expect to see a lower substantiation rate at higher temperatures (assuming in the latter two cases the allegations are not substantiated). By contrast, if low temperatures affect the ability of CPS to successfully substantiate a case, for example by affecting their ability to conduct home visits (e.g., on snowy days), then we might expect substantiation rates to increase with temperatures. Figure 2c depicts the estimated relationship between temperature and the substantiation rates. The estimated coefficients on the hot temperature variables are close to zero and statistically insignificant. The results for cold temperatures are noisier but overall we fail to find compelling evidence of a temperature-substantiation rate relationship, suggesting that our results are not merely reflecting changes in the reporting of child maltreatment at different temperatures.

Thus far in our analysis, the two main outcome measures, the allegation and the victimization rates, reflect all reports of maltreatment of children ages 0 to 4, regardless of the report source. We can learn more about the 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 first explore this question by differentiating between professional and non-professional report sources. Professional reporters include educational, law, and medical personnel among other categories of likely mandatory reporters. Non-professional reporters include neighbors, friends, etc.[18] We use this distinction to create allegation and victimization rate measures by report source. Figure 3 shows results, focusing on the estimated coefficients and 95% confidence intervals for the contemporaneous temperature variables.[19] The left-hand panels report results for the allegation rate while the right-hand panels show results for the victimization rate. The pattern of results is similar across all four panels, with increased child maltreatment at higher temperatures. Thus, we do not find strong evidence of a differential impact of temperatures on child maltreatment when we distinguish by broad reporter category.

Next, we further differentiate among categories of professional reporters as a child's exposure to different types of mandatory reporters may vary with temperature. For example, young children may be less likely to be in pre-school or daycare in the summer months when temperatures are higher, thus reducing their exposure to educational personnel. Figure 4

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

[19]The model includes the temperature lead and lag variables but they are excluded from the figure to highlight the estimated coefficients of interest.

shows the estimated relationship between temperature and the victimization rate for four types of professional reporters.[20] We fail to detect increased victimization rates with higher temperatures for three of the four professional reporter types: social services, education, and medical personnel. For law enforcement personnel, however, the results in Panel 4d are similar to our main results. Evaluated at the mean victimization rate for reports from law enforcement, the estimated coefficient on the 35+ temperature bin variable represents about a 2% increase. Notably, law enforcement is the largest reporting source among professional reporters (Table A1). The pattern of results depicted in Figure 4d could arise both if strangers call law enforcement, for example upon seeing an unattended child; or if law enforcement are investigating a crime scene at which children are present, for example if law enforcement is called to intervene in a case of intimate partner violence or to investigate a drug manufacturing operation, both of which would likely result in an allegation and potential substantiation of child neglect. Note that the patterns we observe are unlikely to be driven by increased police presence on hot days as Obradovich et al. (2018) find that high temperatures decrease police activity (e.g., traffic stops).

Having established that changes in reporting alone are not the main drivers of our estimated effects of hot temperatures on maltreatment, we explore what types of maltreatment are most affected by heat. Because heat has documented effects on aggression and mood, as well as on cognitive function, hotter 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 5 shows the estimated relationship between contemporaneous temperature and the victimization rate for three types of child maltreatment: physical abuse, neglect, and sexual abuse.[21] We find no evidence of increased physical or sexual abuse at high temperatures (Figures 5a and 5c, respectively). Rather, Figure 5b shows that the estimated effects of hot temperatures on maltreatment of young children reported in Figure 2 are driven by increased neglect, the most common maltreatment type.

Finally, we examine whether our estimated maltreatment effects are due to changes in the intensive or extensive margin; do hot temperatures increase maltreatment of children already engaged with CPS or do they bring new children into the CPS system? While we are unaware of estimates that parse the costs to children of CPS engagement and the costs to children of child maltreatment, proponents of abolishing the CPS system argue the former costs are substantial, in particular for Black children (Roberts, 2022). If this is the case, then exploring the intensive and extensive margin responses is important for understanding the overall and

[20] Figure A8 shows results for the allegation rate.
[21] Figure A9 shows results for the allegation rate.

distributional implications of heat exposure. 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.[22] Figure 6 shows that the overall estimated effects of hot temperatures on child maltreatment we find are driven by increased "first incidents". The estimated coefficients on the hot temperature bin variables for prior victims of maltreatment (panels (a) and (b)) are positive but smaller and not statistically different from zero.

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).[23] 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 7 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 find no substantial differences in the temperature-maltreatment relationships for counties below and above the median air conditioning penetration rate. Thus, at least based on this historical measure, we fail to detect a moderating impact of air conditioning. This result reinforces our earlier null findings for physical abuse. If our main results were driven by parents becoming more physically aggressive towards children when temperatures are high (and that behavior resulted in child maltreatment allegations and/or substantiations), then we might expect to see a moderating effect of air conditioning, which we do not detect. Of course it's also possible that air conditioning could mitigate cognitive effects or changes in parenting behaviors and time use that result in neglect but we do not find evidence of this. Our finding of no adaptation in the child maltreatment context is consistent with Mullins and White (2019),

[22] The NCANDS variable we use for this information, chprior, 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.

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

who estimate a stable relationship between temperature and mental health outcomes across different levels of air conditioning penetration.

We next examine whether the child maltreatment-temperature relationship varies with parental exposure to hot temperatures at work. A number of studies document the impacts of occupational heat exposure on various outcomes including time allocation (Graff Zivin and Neidell, 2014; Neidell et al., 2021) and workplace injuries (Park et al., 2021). To explore this mechanism in our context, we use data from the 2005 American Community Survey (ACS) to create a county-level measure of occupational heat exposure. To so do we first characterize industries as high or low exposure following Graff Zivin and Neidell (2014). Second, we use the ACS data, which cover 248 of sample counties, to calculate the share of workers in 2005 in each county who are employed in a high exposure industry. Finally, we create an indicator variable that equals one if a county's share measure exceeds the median and form interactions between this indicator variable and the contemporaneous temperature bins. Figure A10 reports the estimated coefficients and 95% confidence intervals for the contemporaneous temperature variables, which reflect the estimated effects in "low-exposure counties" (circles); and sums of these estimated coefficients and those on the interaction terms, which together capture estimated effects in "high-exposure" counties (diamonds). As with air conditioning above, we find no substantial differences in the temperature-maltreatment relationship for counties with higher and lower shares of workers in more heat-exposed industries. This suggests that our results are not driven by parental on-the-job heat exposure.

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 A11 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 A11a (allegation rate) and A11b (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 A11c and A11d: hot temperatures appear to have larger effects in counties with above-median share of children in poverty. By contrast, we do not find heterogeneous effects between counties with below- and above-median unemployment rates. Overall, these results provide some evidence of a stronger temperature-maltreatment relationship among lower income, higher poverty counties.

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 2b provide an estimate of the effect of a county registering the highest daily maximum temperature in a given temperature bin relative to more moderate temperatures (i.e., 15 to 20°C) on the number of children age 0 to 4 with a substantiated maltreatment case per 1,000 on an average day in the bimonthly reporting period; these are the $\hat{\beta}$s we will use in this exercise. Second, we need to compute the county-level future predicted change in the maximum temperature in a bimonthly period, denoted $\Delta\mathbf{C}$. 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 balanced panel sample. The first assumption presumes that no policy that could mitigate this relationship is adopted, a plausible assumption considering, for example, that we find little evidence that air conditioning mitigates the effects of temperature on maltreatment. The second assumption relates to the comparability of our sample of populous counties and those excluded due to masking issues.

To predict $\Delta\mathbf{C}$, we leverage state-of-the-art techniques and climate change projections. We use downscaled climate estimates for the period 2061-2080 from 25 global climate models included in Phase 6 of the Coupled Model Intercomparison Project, or CMIP (Meehl et al., 2007). We focus on monthly maximum temperatures, gridded at 2.5 minutes of a degree (approximately 4 kilometers).[24] To account for well-documented discrepancies between model predictions and measured and modelled current temperatures (Auffhammer et al., 2013; Ortiz-Bobea, 2021), we compute the change between future and historical climate using the same 1970-2000 climate data used to downscale the models' predictions (Fick and Hijmans, 2017). We then add this difference to 1970-2000 grid-level monthly averages of maximum temperature in the PRISM dataset to obtain the future monthly maximum temperature at the grid-level. Using county centroids, we construct projections of county-level maximum

[24] We use estimates from the following models: ACCESS-CM2, ACCESS-ESM1-5, AWI-CM-1-1-MR, BCC-CSM2-MR, CanESM5, CanESM5-CanOE, CMCC-ESM2, CNRM-CM6-1, CNRM-CM6-1-HR, CNRM-ESM2-1, EC-Earth3-Veg, EC-Earth3-Veg-LR, FIO-ESM-2-0, GISS-E2-1-G, GISS-E2-1-H, HadGEM3-GC31-LL, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MIROC-ES2L, MIROC6, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, UKESM1-0-LL. We downloaded these estimates from `https://www.worldclim.org/` using the function `cmip6` in the R package `geodata`. 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).

temperatures in each reporting period (constant within month) and finally construct $\Delta\mathbf{C}$.

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 25 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 25 climate models, to allow for uncertainty in the climate projections. Thus, this exercise yields a vector of 25,000 bootstrap replications for each county, which reflect both sources of uncertainty.

Figure 8 plots the results of this exercise, extrapolating to 3,076 counties in the contiguous United States for which we have climate data.[25] It reports the estimated net change in the average daily 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 25 climate models we use. We estimate that over the period 2061-2080, climate change will lead to an average increase of 0.007 children aged 0-4 in 1,000 with a substantiated maltreatment case per county-day, an increase of 13% over the current mean. 95% of our 25,000 estimates fall in the 0.0002-0.0361 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 8 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 incidence of maltreatment of young children, with no evidence of differential reporting or substantiation during hotter periods.

[25] Estimates are virtually indistinguishable when we focus on the set of counties in our analysis sample.

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 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 of 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, or allowing them to play outdoors unattended in ways that could place them in danger (such as near a busy road). This story is supported by our findings that (1) reports from law enforcement were the only professional reporter category to be responsive to hot temperatures and (2) that the biggest increases were among children in families who had not previously interacted with the child welfare system. Inattentive parenting could result from changes in time use (for example, parents changing their work schedules) 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.

In order to better understand the mechanisms behind our findings, it would be useful to study the direct effects of temperatures on parent and child time use and on the sources and quality of childcare that families use. McCormack (2023) finds increases in absences among school-aged children on warmer days, suggesting that families are indeed changing their behavior when the weather is warm.

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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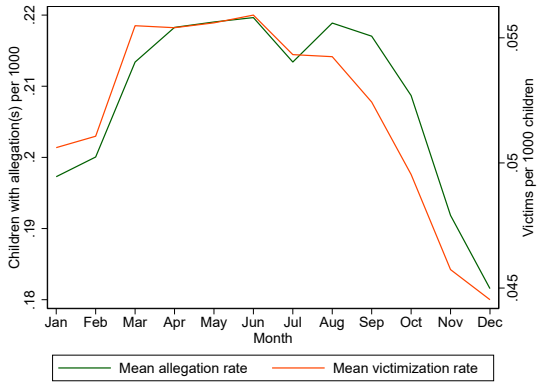
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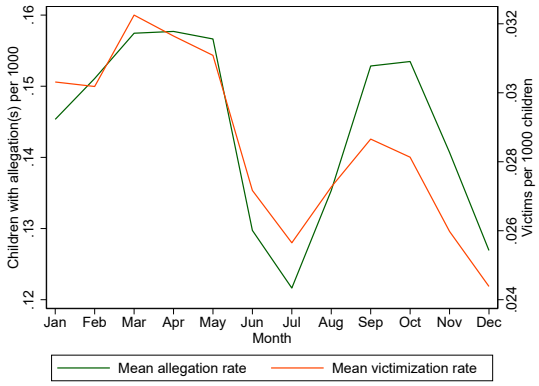
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Figures and Tables

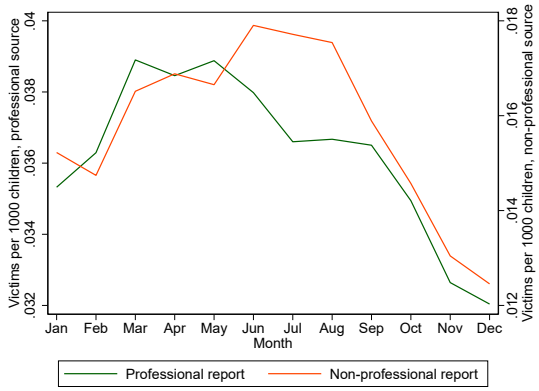
Figure 1: Seasonal Variation in Child Maltreatment by Age and Report Source



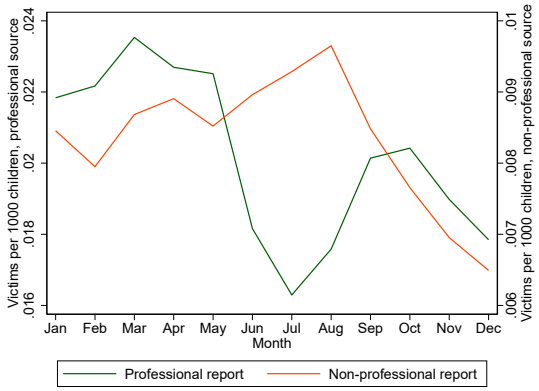
(a) Age 0-4



(b) Age 5-17



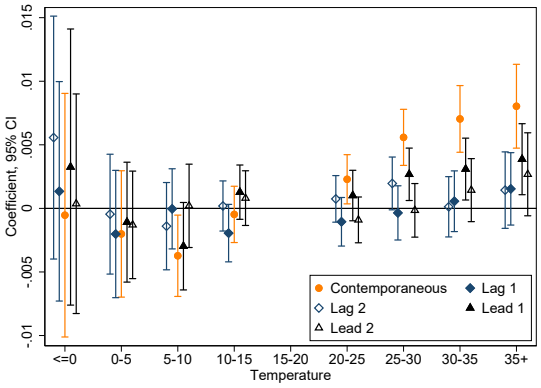
(c) Age 0-4, by report source



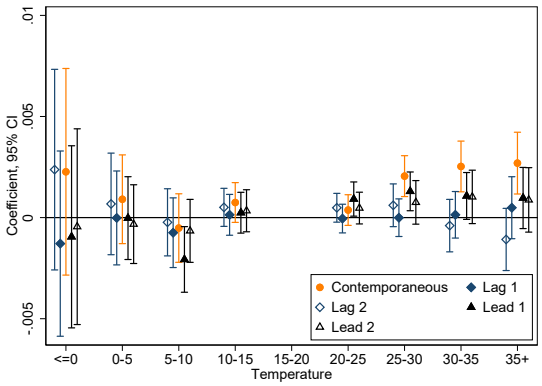
(d) Age 5-17, by report source

NOTES: Panels (a) and (b) of this figure plot the bimonthly means of allegation and victimization rates in the NCANDS data during the sample period, 2006 to 2016 for young children (panel (a)) and school-aged children (panel (b)). The allegation rate measures the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. The victimization rate measures the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period. Panels (c) and (d) plot monthly means of the victimization rate by report source category for children 0-4 and 5-17, respectively.

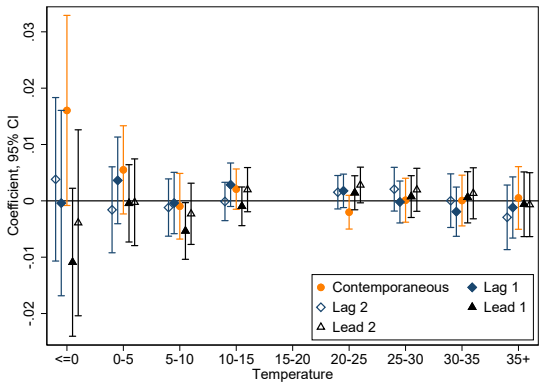
Figure 2: Relationship between Temperature and Maltreatment of Young Children



(a) Allegation rate



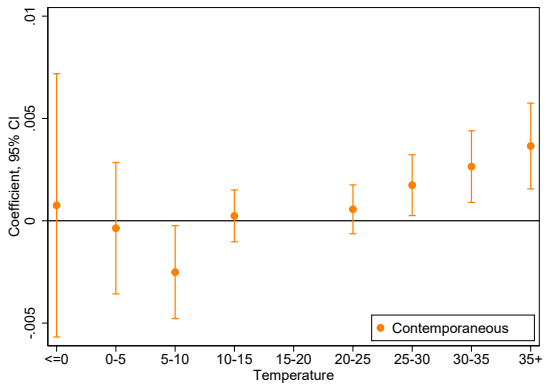
(b) Victimization rate



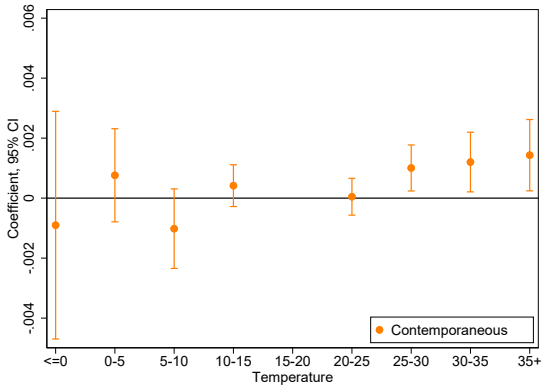
(c) Substantiation rate

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 daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. The sample mean (standard deviation) allegation rate is 0.208 (0.127). Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period. The sample mean (standard deviation) victimization rate is 0.0521 (0.0476). Panel (c) shows results for the substantiation rate, the fraction of children 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 0.255 (0.156).

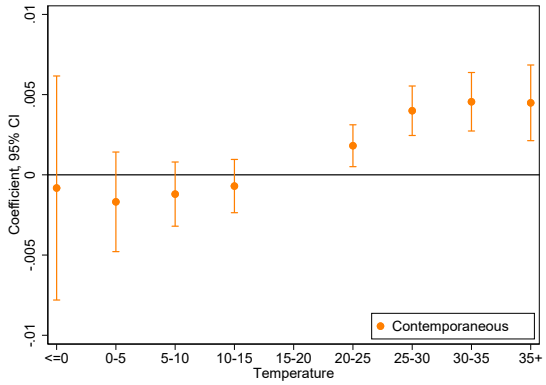
Figure 3: Relationship between Temperature and Maltreatment of Young Children by Report Source



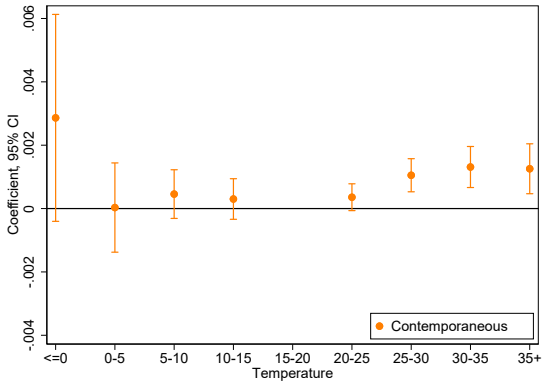
(a) Allegation rate, professional



(b) Victimization rate, professional



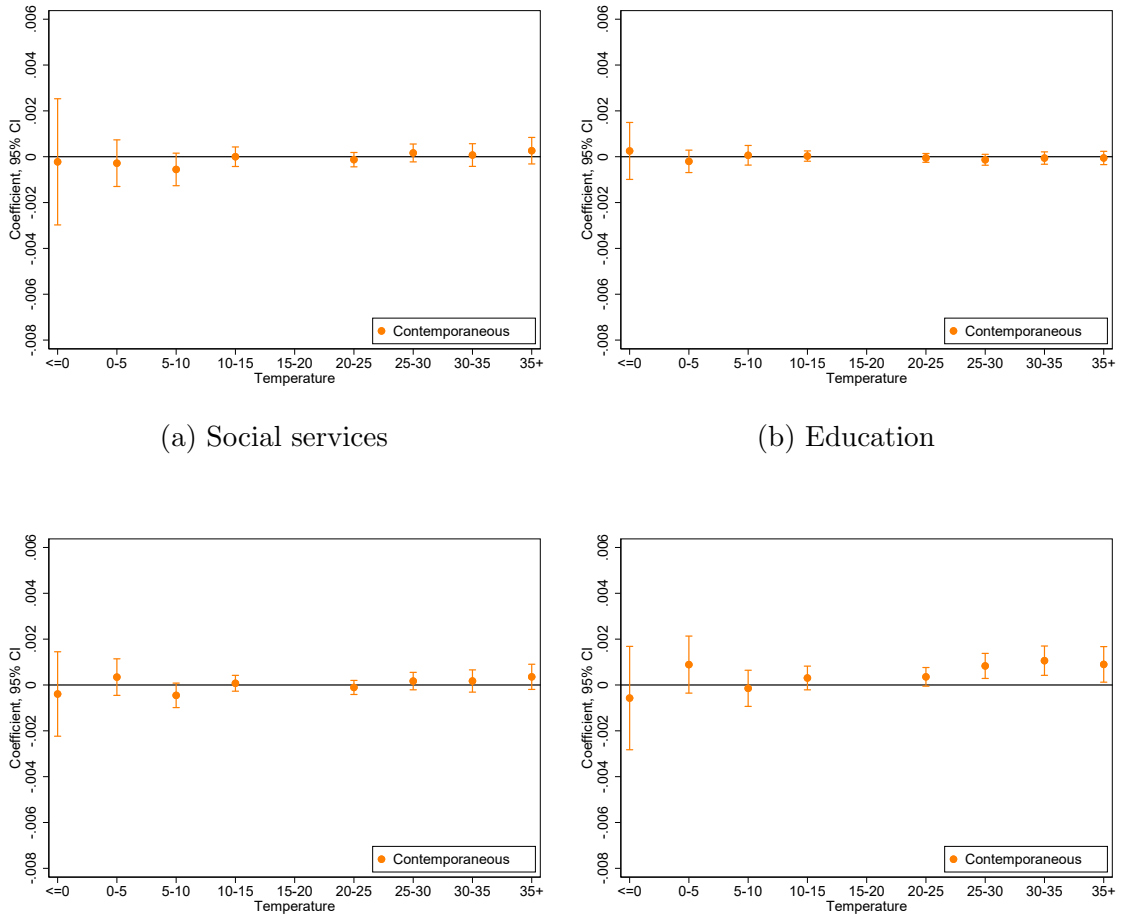
(c) Allegation rate, non-professional



(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 daily average number of children 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 daily average number of children 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 4: Relationship between Temperature and Victimization Rate of Young Children by Professional Report Source



(a) Social services

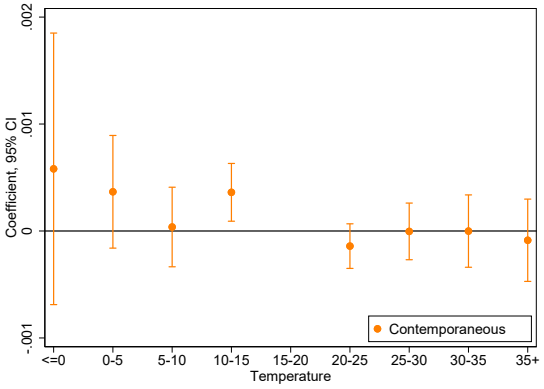
(b) Education

(c) Medical

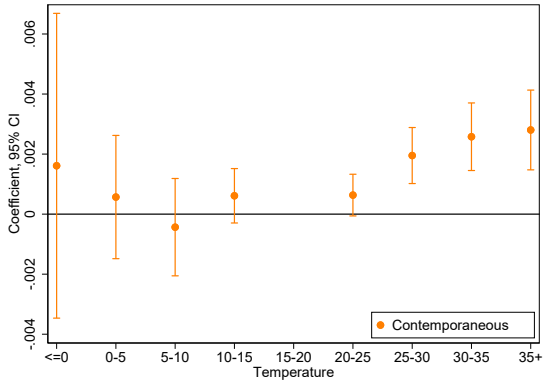
(d) Law enforcement

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 using reports from each specific report source. Panel (a) uses reports from social service personnel; panel (b) is restricted to reports from education personnel and day care providers; panel (c) uses reports from medical and mental health personnel; panel (d) is restricted to reports from legal, law enforcement, and criminal justice personnel. The victimization rate is the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

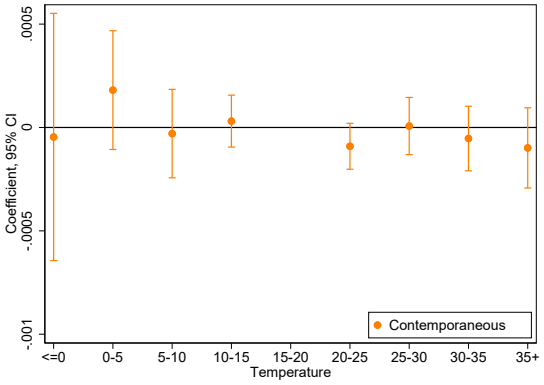
Figure 5: Relationship between Temperature and Victimization Rate of Young Children by Maltreatment Type



(a) Physical abuse



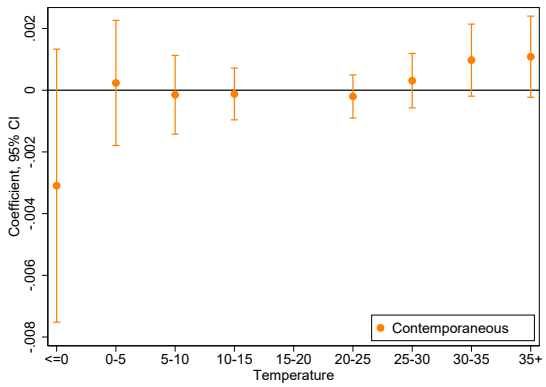
(b) Neglect



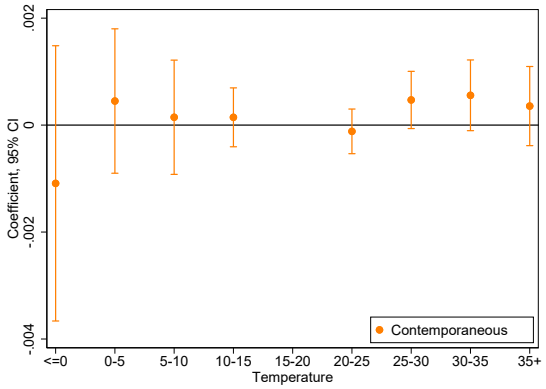
(c) Sexual abuse

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 daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

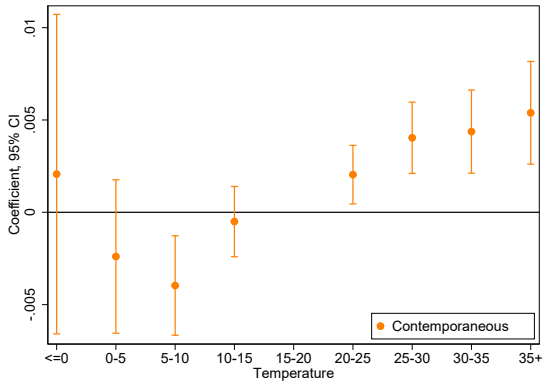
Figure 6: Relationship between Temperature and Child Maltreatment for Young Children by Prior Victim Status



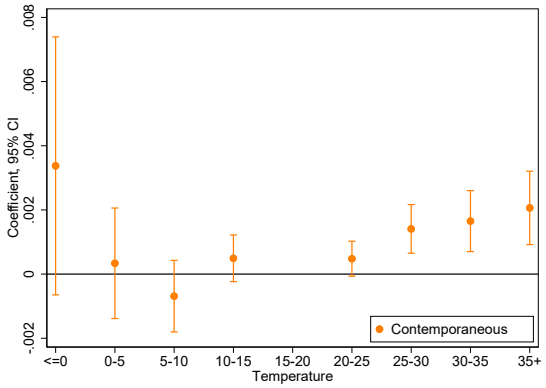
(a) Allegation rate, prior victim



(b) Victimization rate, prior victim



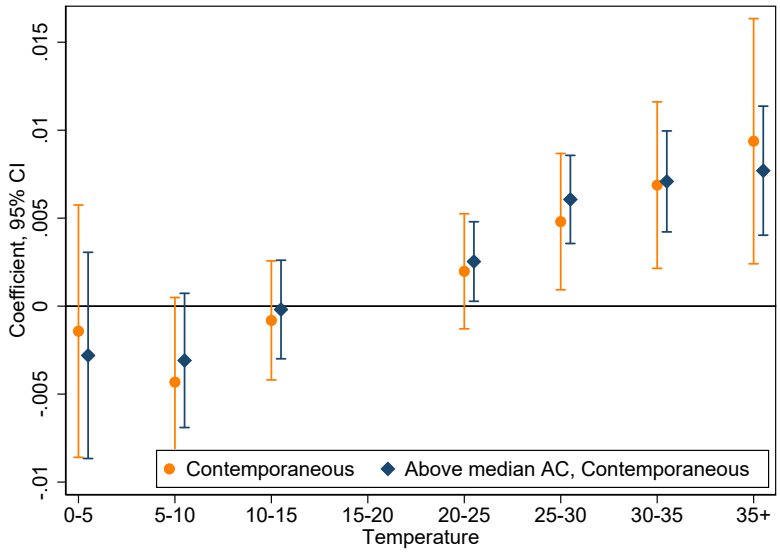
(c) Allegation rate, not prior victim



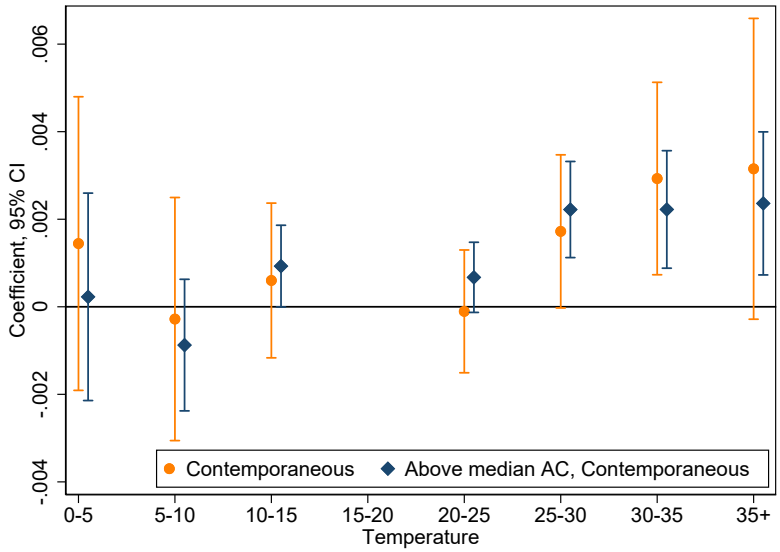
(d) Victimization rate, not prior victim

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Panels (a) and (c) report results for the allegation rate, the daily average number of children 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 daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period. Panels (a) and (b) show results for children who are known to be prior victims of maltreatment while while (c) and (d) depict results for children who are not known to be prior maltreatment victims.

Figure 7: Relationship between Temperature and Maltreatment of Young Children by Air Conditioning Penetration



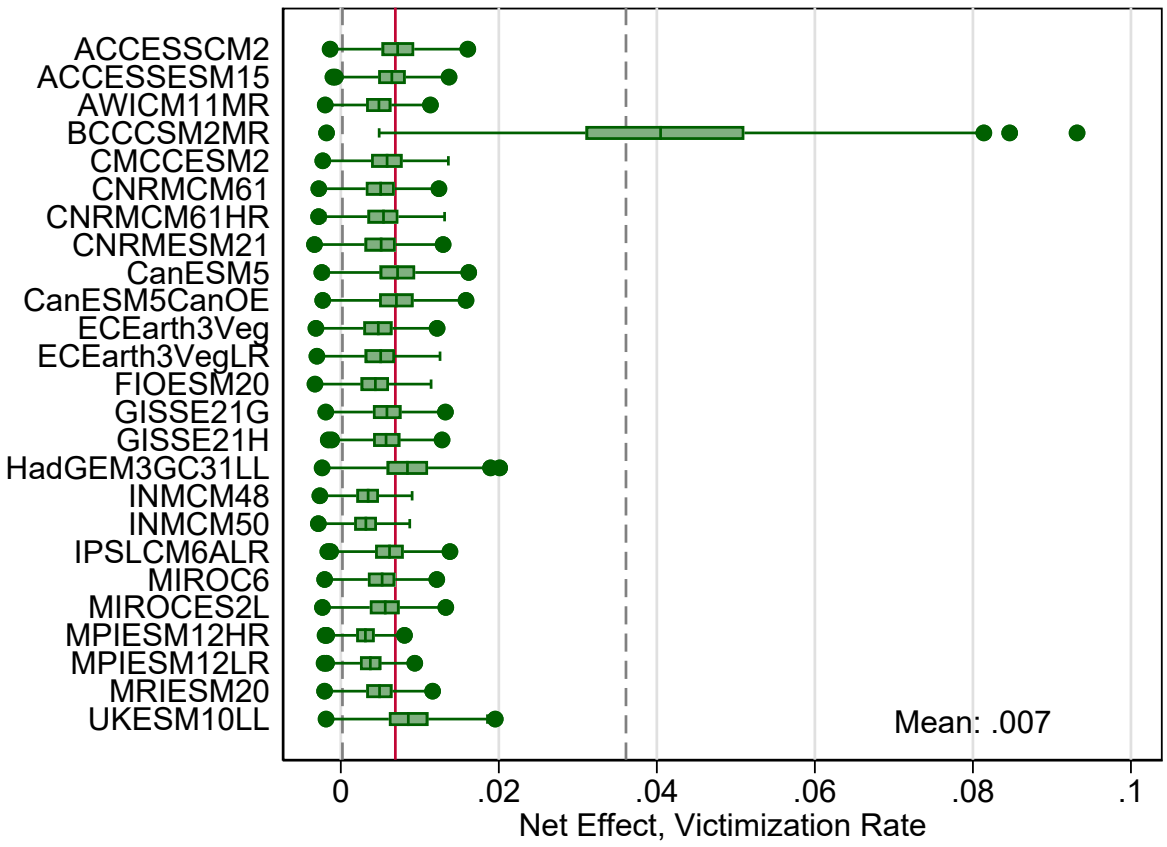
(a) Allegation rate



(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 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. Panel (a) reports results for the allegation rate, the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure 8: Average Predicted Daily Change in Victimization Rate for Young Children in 2061-2080 Due to Climate Change



NOTES: This figure plots the estimated change in the daily victimization rate of children aged 0-4 attributable to climate change, that is the change in the daily average number of children per 1,000 with at least one substantiated maltreatment allegation. It reports results for 25 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 (0.0002 and 0.0361, respectively), while the vertical solid line reports the overall mean, 0.007.

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	0.00803 (0.00168) [0.00185]	0.00679 (0.00158)	0.00730 (0.00147)	0.00701 (0.00145)	0.00834 (0.00171)	0.00824 (0.00171)	0.00606 (0.00108)	0.00545 (0.00145)
Panel B: Victimization rate								
35+ Celsius	0.00269 (0.000778) [0.000823]	0.00247 (0.000725)	0.00265 (0.000658)	0.00253 (0.000657)	0.00288 (0.00836)	0.00267 (0.000798)	0.00164 (0.000411)	0.00164 (0.000622)
County-year & precipitation controls	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
County-month fixed effects	Yes	Yes	No	Yes	No	Yes	Yes	Yes
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
County-bimonthly period	No	No	No	No	Yes	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. 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 111,936 observations, which represent 424 unique counties for 264 bimonthly periods. Alternative sample includes 92,136 observations, which represent 349 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 426 counties 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 17.[26].

The next step in constructing the panel involves appending together all of the relevant Child Files. This results in a data set of 26,307,725 child maltreatment cases reported to CPS agencies between 2006 and 2016, which represents 15,251,185 unique children. As a final step before forming the panel we remove cases for which the maltreatment type was listed as "no alleged maltreatment" (about 12%). This value identifies cases in which a child receives a CPS response but was not the subject of a maltreatment allegation and is used in states that require all children in a household to receive a CPS response if any child in the household is the subject of a CPS response. Within this case-level sample, the median child age is seven; about a third of cases are associated with children age four or younger.

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 (e.g., with at least one allegation, with at least one substantiated allegation, etc.) in the county and bimonthly period. We then divide the resulting counts by the number of days in the bimonthly period and scale by annual child population in the county measured in thousands from SEER. The resulting balanced county-by-bimonthly period panel contains 112,464 observations, which represents 426 unique counties and 264 unique bimonthly reporting periods during the 11-year sample period.

About 7% of cases (prior to collapsing) have missing values for report source and less than a half percent of cases have missing values for maltreatment type. We assign the following

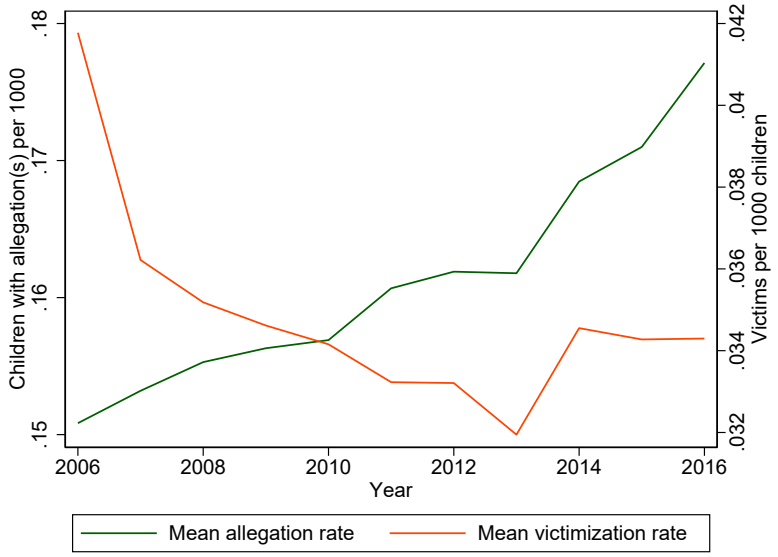
[26]Prior to this final restriction, less than one percent of cases have missing values for child age

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.

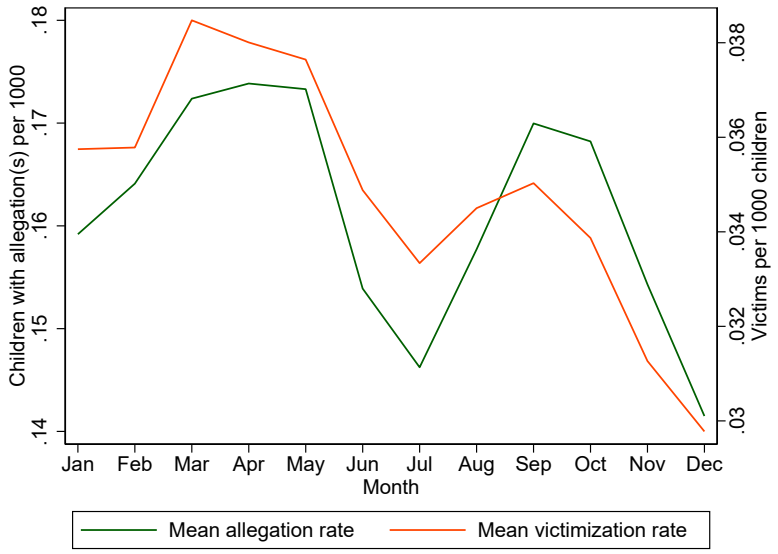
Finally, we drop two counties that do not belong to the contiguous United States as we do not have weather data for them. Thus, we obtain a balanced panel of 424 counties in 42 states.

A.2 Additional figures and tables

Figure A1: Temporal Variation in Child Maltreatment, Age 0-17



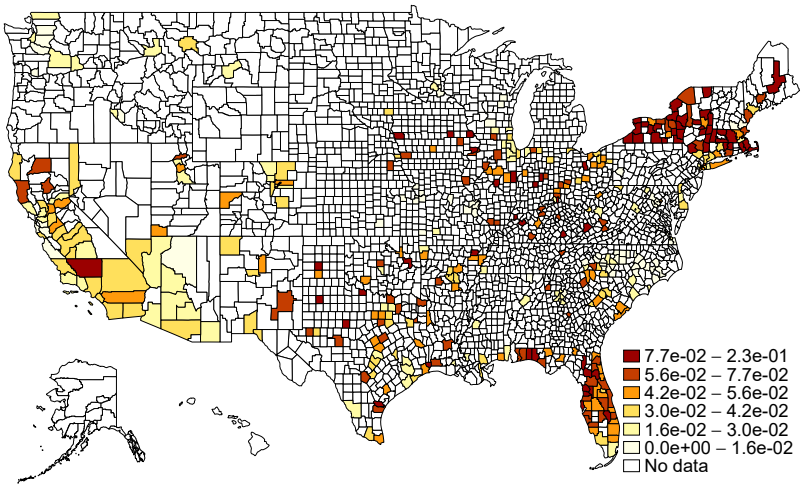
(a) Annual variation



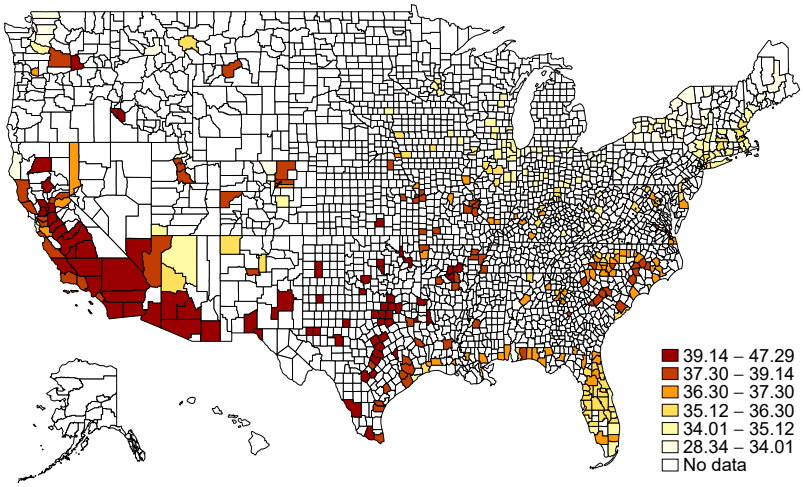
(b) Monthly

NOTES: This figure plots the annual (panel (a)) and monthly (panel (b)) means of the daily average allegation (left y-axis) and victimization (right y-axis) rates in the bimonthly period for the sample period, 2006 to 2016. The daily average allegation rate measures the average number of children per 1,000 with at least one maltreatment allegation in each day during the bimonthly reporting period. The daily average victimization rate measures the average number of children per 1,000 with at least one substantiated maltreatment allegation in each day during the bimonthly reporting period.

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



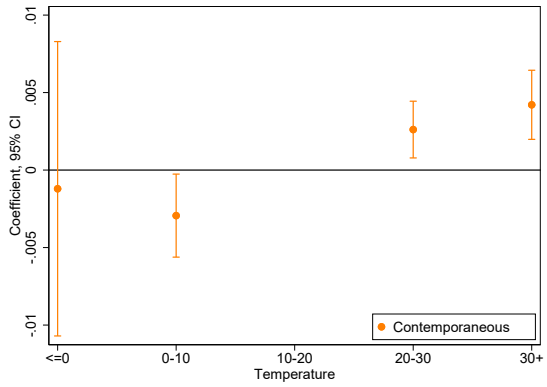
(a) Median victimization rate



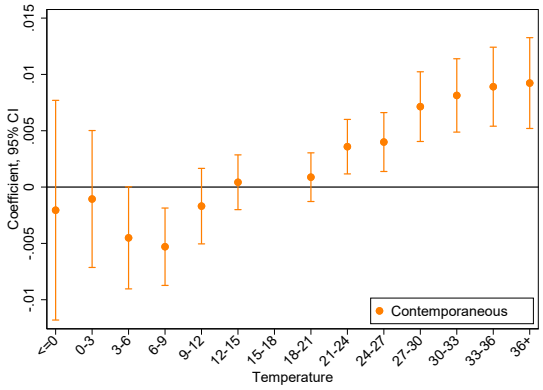
(b) Average temperature

NOTES: This figure depicts spatial variation in victimization rates and temperatures. Panel (a) plots the median of the daily average victimization rates for young children in the bimonthly period for the sample period, 2006 to 2016. The daily average victimization rate measures the average number of children age 0-4 per 1,000 with at least one substantiated maltreatment allegation in each day during the bimonthly reporting period. Panel (b) shows the maximum yearly temperature recorded in each county averaged over the years in our sample: 2006-2016.

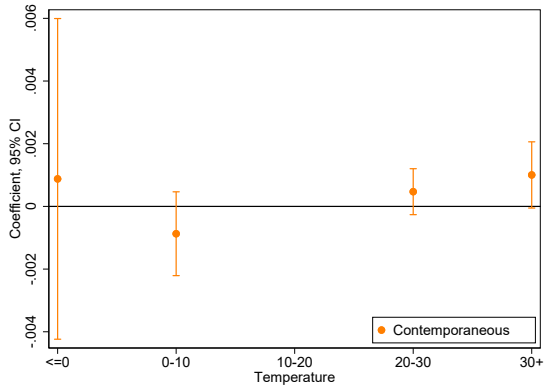
Figure A3: Relationship between Temperature and Maltreatment of Young Children, Alternative Temperature Bins



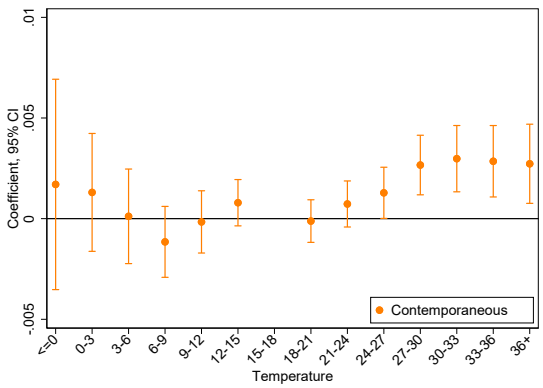
(a) Allegation rate: 10-degree bins



(b) Allegation rate: 3-degree bins



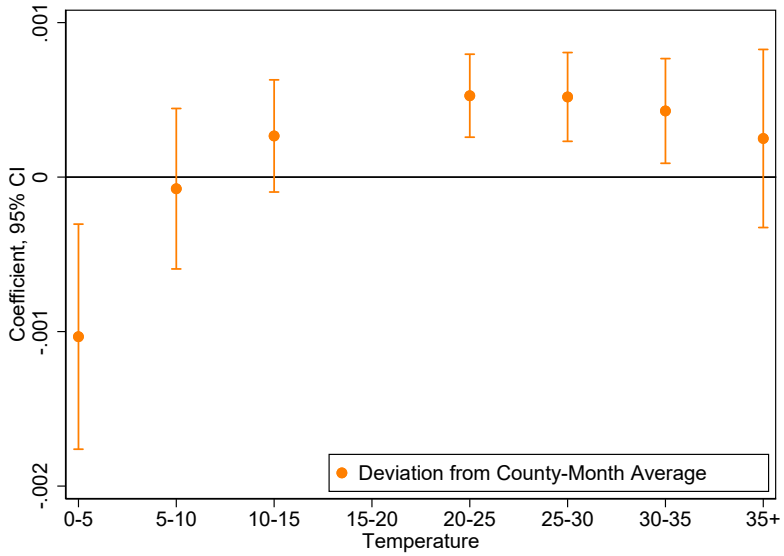
(c) Victimization rate: 10-degree bins



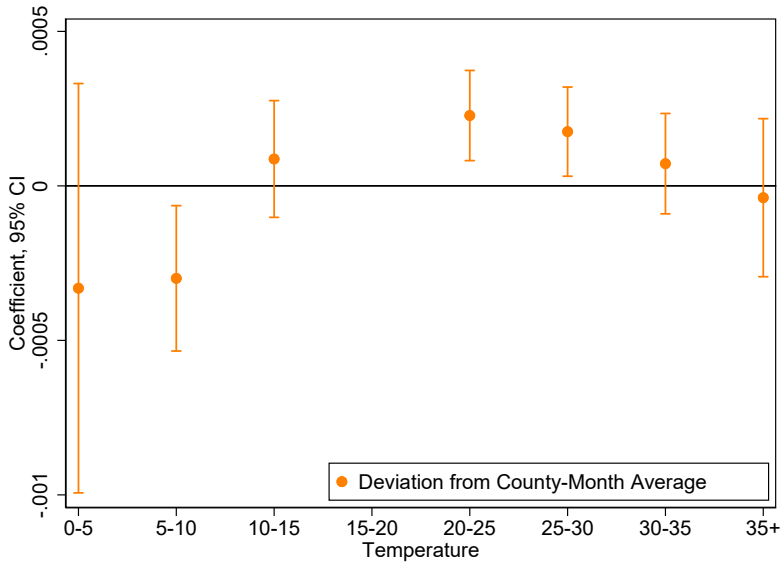
(d) Victimization rate: 3-degree bins

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 daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panels (c) and (d) plot results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure A4: Relationship between Temperature and Maltreatment of Young Children, Deviations from County-Bimonthly Averages



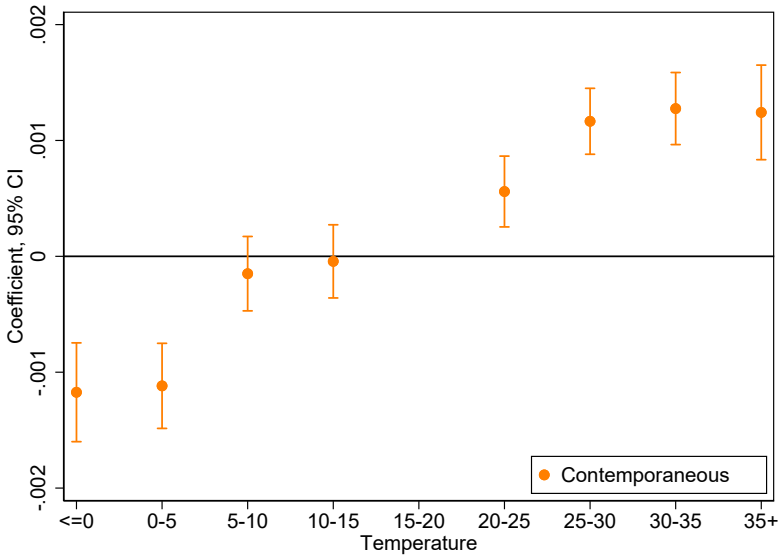
(a) Allegation rate



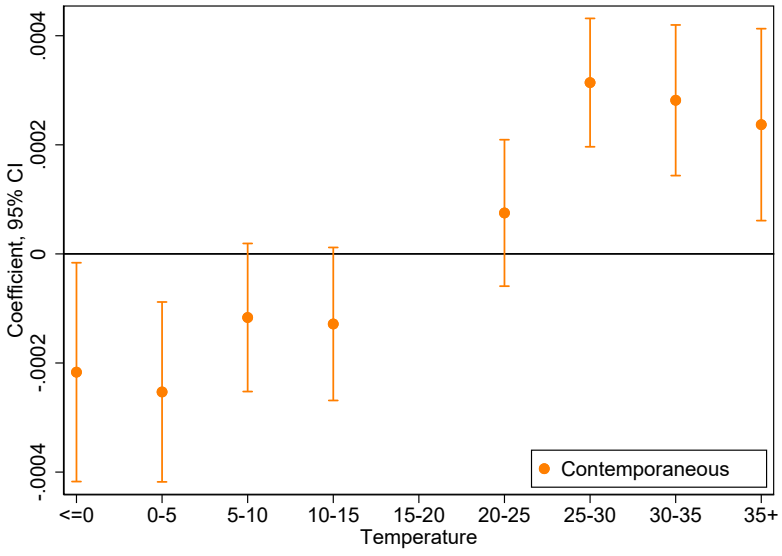
(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on interaction terms of binned "normal" maximum temperatures in a county-period and the contemporaneous deviation of maximum temperature from this "normal". For each county-bimonthly reporting period, the "normal" temperature is the average of the maximum daily temperature at the county and biweekly reporting period across years in our sample period. For each county-period, the contemporaneous deviation is the difference between the actual maximum of the daily maximum temperatures during each reporting period and this "normal" maximum temperature for that county and peariod of the year. Controls and fixed effects are as described in the main specification. Panel (a) reports results for the allegation rate, the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure A5: Relationship between Temperature and Maltreatment of Young Children, Count of Days in Temperature Range



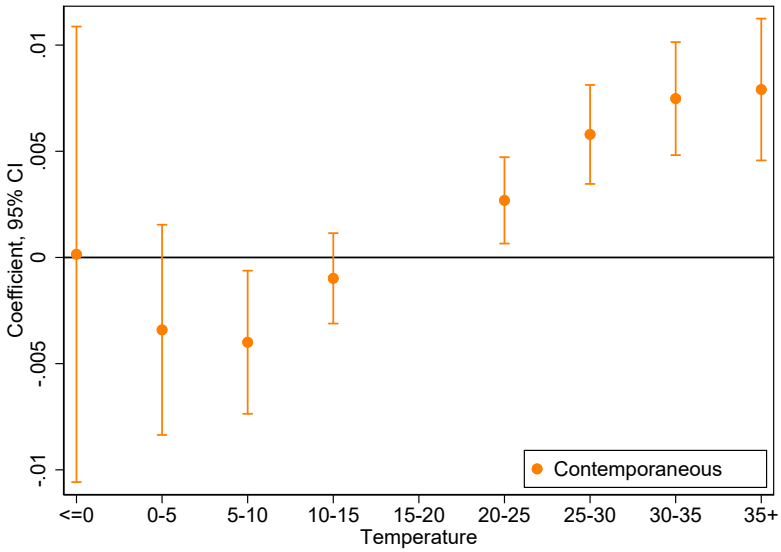
(a) Allegation rate



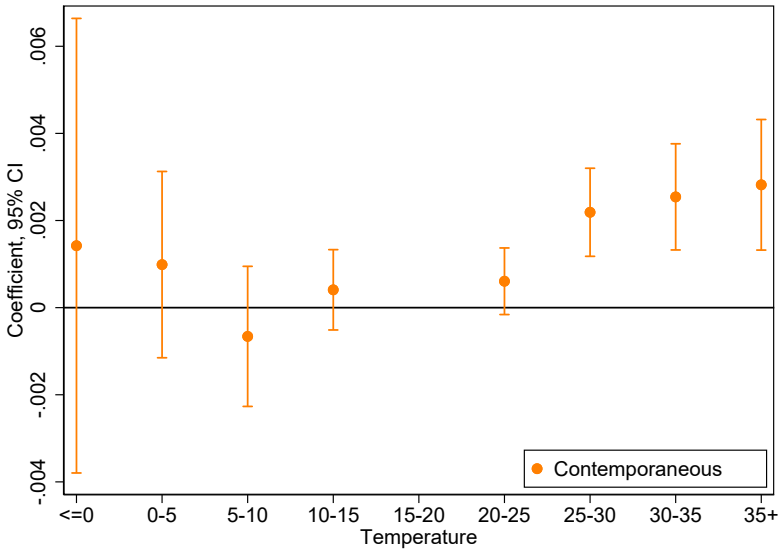
(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on contemporaneous temperature bin variables where each variable measures the number of days during the county-bimonthly reporting period on which the maximum daily temperature is within the respective temperature range. Temperature leads and lags, defined similarly, 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 daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

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



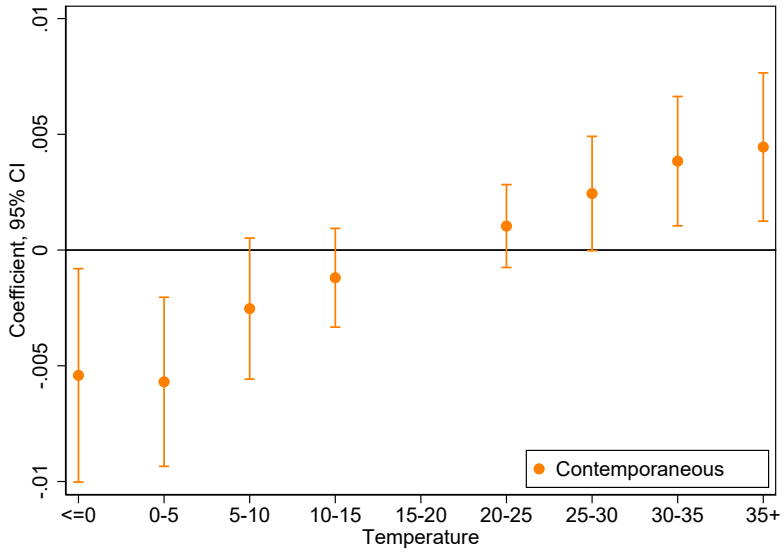
(a) Allegation rate



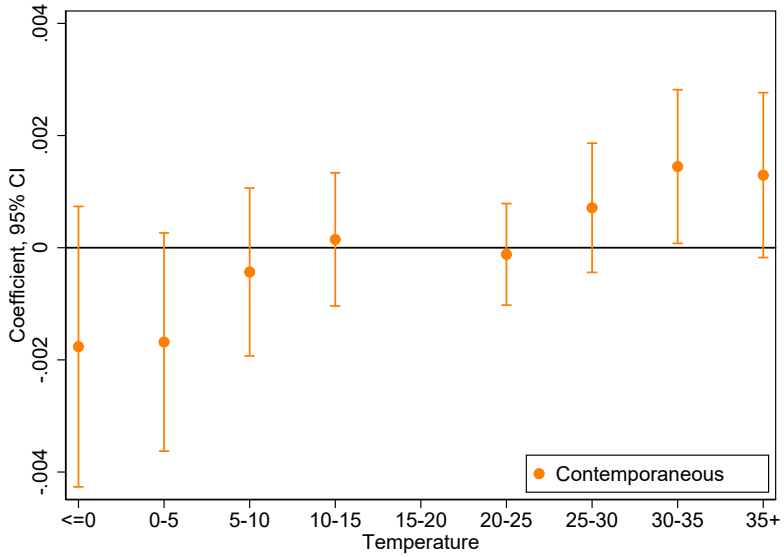
(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the contemporaneous temperature bin variables. Temperature leads and lags are included but not reported. Controls and fixed effects are as described in the main specification. Panel (a) reports results for the allegation rate, the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children 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 A7: Relationship between Temperature and Maltreatment of Young Children, Alternative Temperature Data



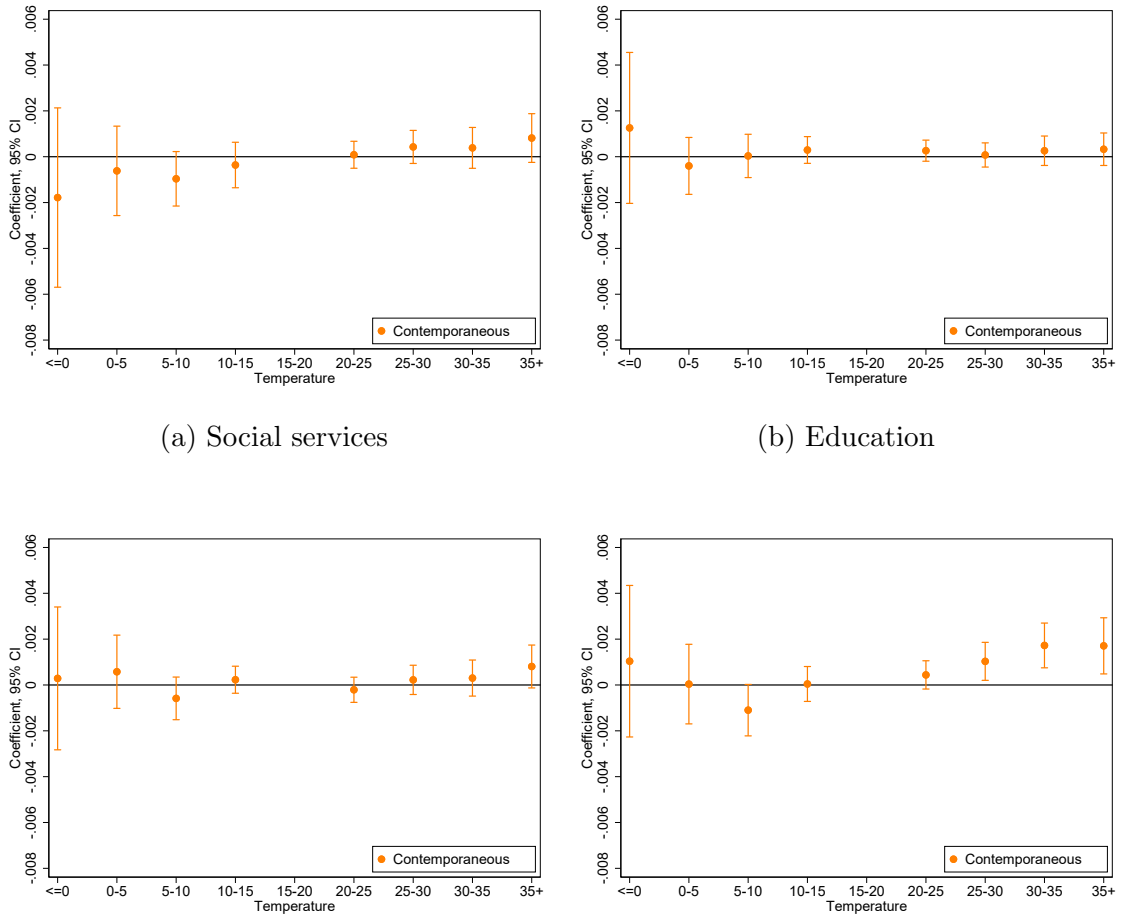
(a) Allegation rate



(b) Victimization rate

NOTES: This figure plots the estimated coefficients and 95% confidence intervals on the temperature bin variables in the main specification where temperature is measured using MODIS data. Panel (a) reports results for the allegation rate, the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

Figure A8: Relationship between Temperature and Allegation Rate for Young Children by Professional Report Source



(a) Social services

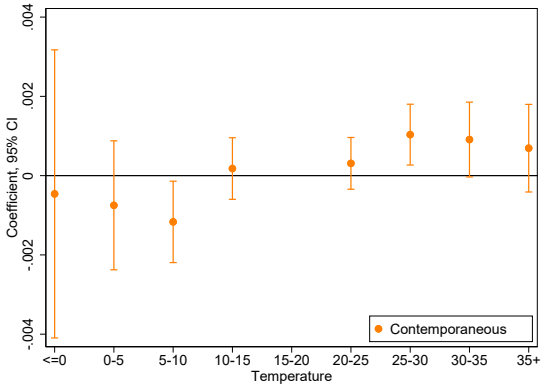
(b) Education

(c) Medical

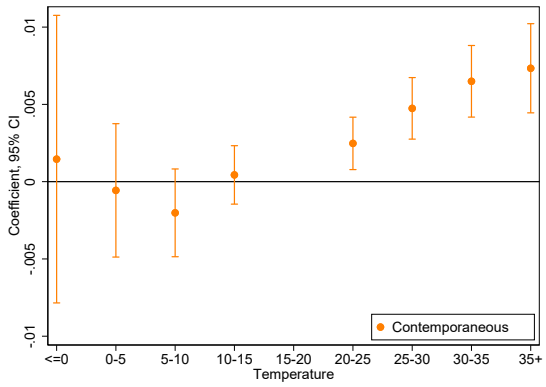
(d) Law enforcement

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 using reports from each specific report source. Panel (a) uses reports from social service personnel; panel (b) is restricted to reports from education personnel and daycare providers; panel (c) uses reports from medical and mental health personnel; panel (d) is restricted to reports from legal, law enforcement, and criminal justice personnel. The allegation rate is the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period.

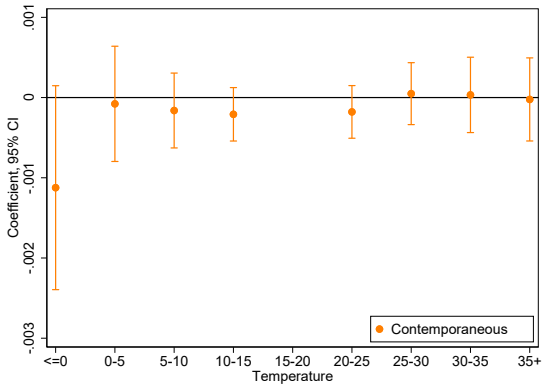
Figure A9: Relationship between Temperature and Allegation Rate for Young Children by Maltreatment Type



(a) Physical abuse



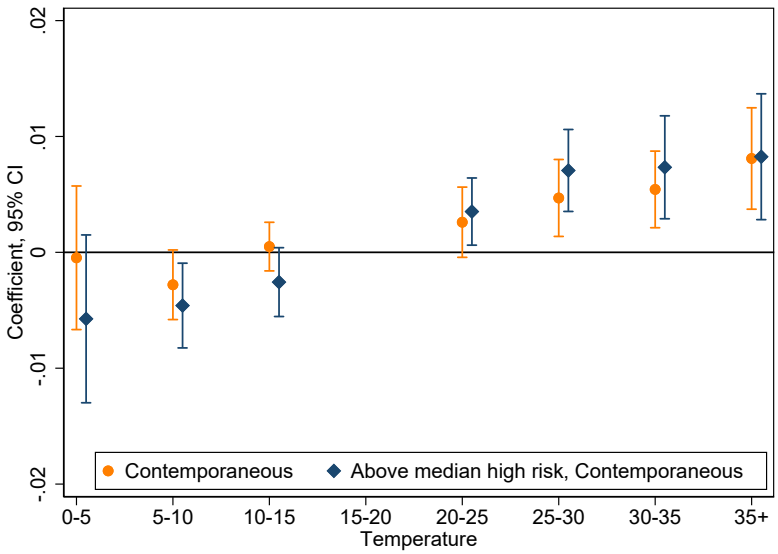
(b) Neglect



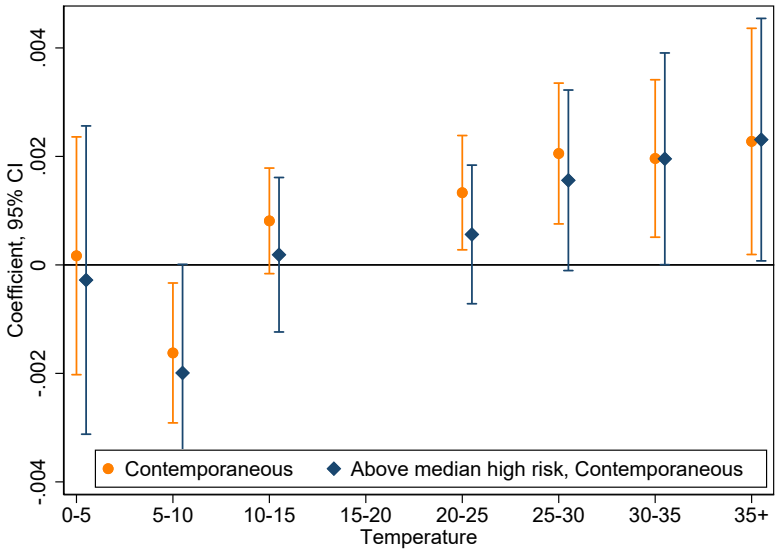
(c) Sexual abuse

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 daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period.

Figure A10: Relationship between Temperature and Maltreatment of Young Children by Occupational Heat Exposure



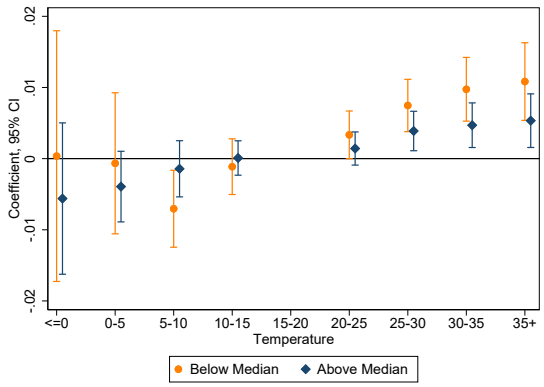
(a) Allegation rate



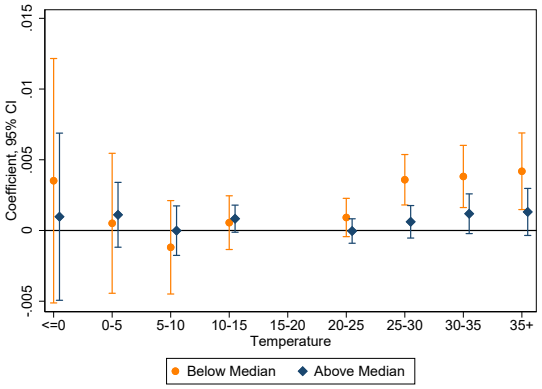
(b) Victimization rate

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 county-level above-median share of employment in high heat exposure industries 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. Panel (a) reports results for the allegation rate, the daily average number of children per 1,000 with at least one maltreatment allegation during the bimonthly reporting period. Panel (b) plots results for the victimization rate, the daily average number of children per 1,000 with at least one substantiated maltreatment allegation during the bimonthly reporting period.

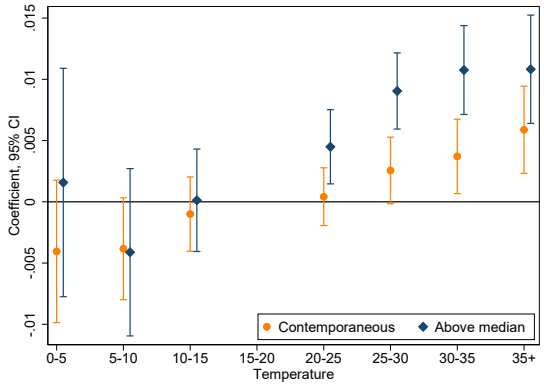
Figure A11: Relationship between Temperature and Maltreatment of Young Children: Heterogeneous Effects



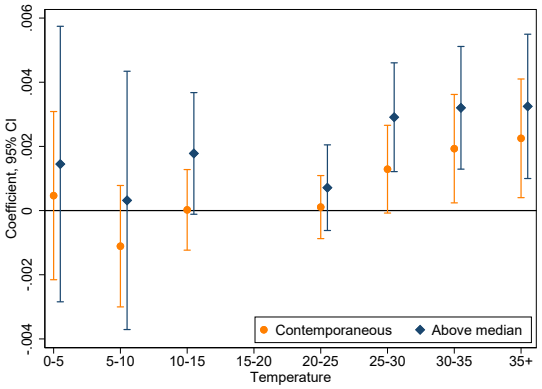
(a) Median HH income, Allegation rate



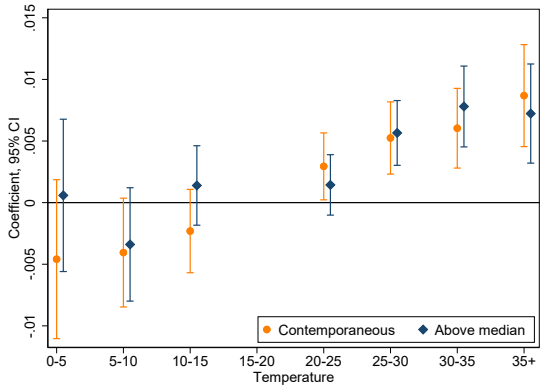
(b) Median HH income, Victimization rate



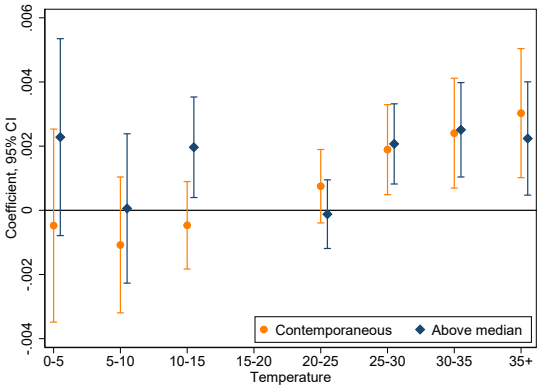
(c) % children in poverty, Allegation rate



(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.

Table A1: Summary Statistics for Outcome Measures

	Mean (Standard deviation)
Panel A: Allegation rate measures	
Allegation rate	0.208 (0.127)
Allegation rate, professional source	0.102 (0.071)
Allegation rate, non-professional source	0.107 (0.084)
Allegation rate, educational source	0.013 (0.017)
Allegation rate, medical source	0.026 (0.024)
Allegation rate, social services source	0.023 (0.027)
Allegation rate, law enforcement source	0.040 (0.038)
Allegation rate, prior victim	0.044 (0.054)
Allegation rate, not prior victim	0.153 (0.105)
Panel B: Victimization rate measures	
Victimization rate	0.052 (0.048)
Victimization rate, professional source	0.036 (0.035)
Victimization rate, non-professional source	0.016 (0.022)
Victimization rate, educational source	0.002 (0.006)
Victimization rate, medical source	0.009 (0.012)
Victimization rate, social services source	0.008 (0.013)
Victimization rate, law enforcement source	0.018 (0.021)
Victimization rate, prior victim	0.014 (0.022)
Victimization rate, not prior victim	0.035 (0.035)

NOTES: Table reports means and standard deviations for outcome measures based on the balanced panel sample of 111,936 observations, which represents 424 unique counties for 264 bimonthly periods. The mean and standard deviation for the substantiation rate are 0.255 and 0.156, respectively. See text at beginning of appendix for information on construction of measures and missing values.

Table A2: Results for Control Variables in Main Specifications

	Allegation rate	Victimization rate	Mean (Standard deviation)
Share of children in poverty	0.0926	0.00277	0.210
	(0.0324)	(0.0166)	(0.074)
Median household income (1,000 2016 USD)	-0.000634	-0.000661	55.079
	(0.000273)	(0.000151)	(13.115)
Share Black	0.398	0.0842	0.120
	(0.201)	(0.105)	(0.120)
Share Hispanic	-0.644	-0.182	0.141
	(0.135)	(0.0851)	(0.156)
Share other race	-0.870	-0.139	0.045
	(0.231)	(0.104)	(0.052)
Unemployment rate	0.000598	0.000222	6.837
	(0.00124)	(0.000575)	(2.722)
Average daily precipitation over reporting period (in decimeters)			
Contemporaneous	-0.0510	-0.0157	0.029
	(0.00766)	(0.00341)	(0.030)
Lag 1	0.00534	0.00106	0.029
	(0.00703)	(0.00359)	(0.030)
Lag 2	0.00368	-0.000559	0.029
	(0.00697)	(0.00310)	(0.030)
Lead 1	0.00773	-0.000617	0.029
	(0.00838)	(0.00359)	(0.030)
Lead 2	0.00217	0.000111	0.029
	(0.00703)	(0.00353)	(0.030)

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 111,936. which represents 424 unique counties for 264 bimonthly periods.