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ABSTRACT

What to Expect When It Gets Hotter: The Impacts of Prenatal Exposure to Extreme Heat on Maternal and Infant Health*

We use temperature variation within narrowly-defined geographic and demographic cells to show that prenatal exposure to extreme heat increases the risk of maternal hospitalization during pregnancy, and that this effect is larger for black than for white mothers. At childbirth, heat-exposed mothers are more likely to have hypertension and have longer hospital stays. For infants, fetal exposure to extreme heat leads to a higher likelihood of dehydration at birth and hospital readmission in the first year of life. Our results provide new estimates of the health costs of climate change and identify environmental drivers of the black-white maternal health gap.

JEL Classification: I14, I18, Q54

Keywords: extreme heat, maternal health, infant health

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1 Introduction

The United States has experienced a deterioration in maternal pregnancy- and childbirth-related health over the last several decades (Kassebaum et al., 2016), and the burden of health complications is not borne equally by all mothers. For instance, black women are 3.3 times more likely to die from a pregnancy-related cause than their white counterparts (Petersen et al., 2019). Most of the discussions about maternal health focus on the role of the health care system, but we know much less about other—*environmental*—determinants of maternal health and the racial disparities in it.[1] This paper focuses on an environmental factor that is becoming increasingly relevant due to the growing consensus that climate change is contributing to a gradual warming of the earth (NASA, 2013): exposure to extreme heat.

A burgeoning literature has identified adverse short-term impacts of extreme temperatures on several population outcomes, including elderly mortality (Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011), emergency department visits and hospitalizations (Green et al., 2010; White, 2017), and cognitive performance (Cho, 2017; Garg et al., 2018; Goodman et al., 2018; Graff Zivin, Hsiang, and Neidell, 2018). Further, two recent studies have shown that *in utero* heat exposure has lasting negative effects on long-term cognitive ability (Hu and Li, 2019) and adult earnings (Isen, Rossin-Slater, and Walker, 2017), highlighting the sensitivity of the prenatal period to extreme heat.[2] To the best of our knowledge, however, no prior studies have identified the causal effects of prenatal exposure to extreme temperatures on *the health of the mothers themselves*, and this paper aims to fill this gap.[3]

Further, the mechanism underlying the relationship between fetal exposure to heat and long-term human capital remains poorly understood. The widely documented association between birth weight and adult outcomes (e.g., Black, Devereux, and Salvanes, 2007; Royer, 2009) suggests that the effect of prenatal temperature exposure may operate at least in part through a heat-induced reduction in birth weight (Deschênes et al., 2009). However, as recent work emphasizes that birth weight provides limited information about the uterine environment (Conti et al., 2018), evidence

[1]For examples of these discussions in the press, see: `https://www.vox.com/science-and-health/2017/6/26/15872734/what-no-one-tells-new-moms-about-what-happens-after-childbirth`
`https://www.npr.org/2017/05/12/528098789/u-s-has-the-worst-rate-of-maternal-deaths-in-the-developed-world`
`https://www.npr.org/2017/05/12/527806002/focus-on-infants-during-childbirth-leaves-u-s-moms-in-danger`.

[2]Fetuses and infants are sensitive to extreme heat due to their developing thermoregulatory and sympathetic nervous systems; see Young (2002); Knobel and Holditch-Davis (2007); Xu et al. (2012).

[3]Kuehn and McCormick (2017) conducted a systematic review of the literature on the effect of extreme heat on pregnancy outcomes globally. They identified 28 studies, which examined a range of birth outcomes, including preterm birth, low birth weight, and stillbirth. However, they did not identify any studies that investigated any measures of *maternal* health during pregnancy or at childbirth. Moreover, most of the medical studies on this topic use time-series variation in temperature to show that rates adverse birth outcomes are higher when temperatures are hot (Dadvand et al., 2011, Auger et al., 2017, Schifano et al., 2016, Ha et al., 2017a,b). We build on this literature by leveraging arguably more random variation in extreme temperature exposure stemming from deviations from trends within narrowly-defined geographic and demographic cells, as we detail below.

on more specific measures of children's health at birth and in infancy may help us open the "black box" of the link between the early life environment and long-term outcomes.

This paper studies the effect of exposure to extreme temperature during pregnancy on maternal and child hospitalizations, using the universe of administrative inpatient discharge records from three U.S. states with different climates: Arizona, New York, and Washington. To identify a causal effect of temperature exposure, we exploit residual temperature variation over time within narrowly-defined geographic and demographic cells. Our preferred specifications control for a full set of birth-county$\times$birth-month$\times$race$\times$sex fixed effects, birth-state$\times$birth-year fixed effects, and a quadratic time trend interacted with county$\times$calendar month indicators. In addition, to account for the substantial variation in average temperatures across geographic regions that could generate differences in adaptation responses (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Barreca et al., 2015; Barreca et al., 2016; Carleton et al., 2018), we model exposure to extreme heat in terms of standard deviations relative to each county's monthly temperature mean.

Our results show that exposure to extreme heat has adverse impacts on women's health during pregnancy. We find that an additional day during the second (third) trimester with average temperature at least three standard deviations above the county's monthly mean (hereafter referred to as "above-3-SD heat") increases the likelihood that a woman is hospitalized during pregnancy by 0.19 (0.12) percentage points, which represents a 4.8 (3.0) percent effect at the sample mean. The estimated deterioration in pregnancy health is larger for black women than for white women, both in absolute and relative terms. For black women, an additional day with above-3-SD heat during pregnancy raises the likelihood of hospitalization by 0.3 percentage points, or 5.0 percent. For white women, the corresponding magnitude is a 0.1 percentage point increase, or 2.6 percent.

We also demonstrate that extreme heat during pregnancy leads to worse maternal health at the time of childbirth. An additional day with above-3-SD heat in the first trimester raises the probability of a complication at childbirth by 0.48 percentage points (1.0 percent). An additional day of extreme heat in the third trimester increases the likelihood of a hypertension diagnosis at childbirth by 0.2 percentage points (2.9 percent) and increases maternal length of stay at the hospital by a (marginally significant) 0.009 days (0.3 percent).

Lastly, we present evidence of adverse impacts of extreme heat on novel measures of infant health. We show that an additional day with above-3-SD heat during the second trimester increases the likelihood of a newborn being diagnosed with dehydration by 0.008 percentage points (31 percent) and increases the probability that the infant is readmitted to the hospital within the first year of life by 0.3 percentage points (3.4 percent). We find that the increase in re-hospitalizations is driven by diagnoses for prenatal jaundice, prenatal hematological disorders, and respiratory diseases, which is consistent with a medical literature that identifies a link between infant dehydration and future childhood diseases (e.g., Steiner et al., 2004; Green et al., 2010).

Our findings suggest that, in the absence of mitigating interventions, the projected increase in exposure to extreme heat over the next century may contribute to further worsening of maternal health. Moreover, since black women are both more likely to be exposed to extreme heat (due to differences in residence locations and in access to mitigating technologies such as air conditioning, see O'Neill et al., 2005; Gronlund, 2014) and experience larger adverse impacts of heat exposure on pregnancy-related health, our estimates imply that climate change could further exacerbate racial disparities in maternal health.

Our results on infant diagnoses and hospital re-admissions provide more nuanced measures of health impacts that may not be captured by commonly used markers such as birth weight. These estimates shed light on the possible mechanism through which fetal exposure to extreme heat could negatively affect later adult outcomes (Isen et al., 2017; Hu and Li, 2019): children who are exposed to unusually hot temperatures *in utero* are more likely to be dehydrated at birth and experience health complications during infancy, which may inhibit their ability to develop cognitive and non-cognitive skills that support long-term human capital formation (Cunha and Heckman, 2007; Heckman and Mosso, 2014).

2 Data

Our data comes from the State Inpatient Databases (SID) from the Healthcare Cost and Utilization Project (HCUP). The SID are state-specific files that contain the universe of inpatient records from participating states. Since the availability of variables varies across states and years, we focus on three states that contain all three of the key variables necessary for our analysis: (1) patient county of residence, (2) admission month, and (3) encrypted person identifiers to track patients over time in the same state. Our resulting sample consists of 2.73 million inpatient records of 2.68 million infants and 2.72 million inpatient records of 2.24 million mothers from Arizona (2003 to 2007), New York (2003 to 2013), and Washington (2003 to 2013).

We use diagnosis codes to identify inpatient visits associated with delivery (for mothers) and birth (for infants).[4] Since less than two percent of all births occur outside of hospitals during our analysis time period, we observe the near-universe of all mothers and infants in our analysis states.[5] We also identify maternal hospitalizations during pregnancy (i.e., those occurring in the 9 months before delivery) and hospital re-admissions for infants using patient identifiers.

To measure temperature exposure, we obtain data from the National Oceanic and Atmospheric Administration (NOAA). We have information on the mean, maximum, and minimum daily ground temperature and precipitation levels for every county and year-month during our analysis time frame. We then merge these data to the maternal and child inpatient records, using information on the mother's county of residence at the time of delivery and the child's county of birth, respectively. We use the child's birth year and month (or the mother's year and month of delivery) to

[4]We use DRG 370-375 or 765-768 & 774-775, depending on the version of DRG. Our data do not allow us to link mothers to their own children, but we examine them separately.

[5]See `https://www.cdc.gov/nchs/products/databriefs/db144.htm` for statistics on out-of-hospital births in the U.S.

assign exposure to temperature during pregnancy by assuming a 40-week pregnancy duration for all observations.[6]

To account for the large amount of variation in average temperatures across different geographic areas, we normalize temperature relative to the overall average in each county-by-calendar-month. Specifically, we first calculate the average temperature for every county-month (e.g., July in Queens county, NY), using data from all available years. Then, for every month in all county-year combinations (e.g., July 2012 in Queens county, NY), we calculate the difference between the given month's mean temperature and the overall average for that county-month, and divide by the standard deviation. We thus obtain a z-score that allows us to classify each month in any given county-year based on its deviation from the overall county-month average. We denote a month in which the mean temperature is at least 3 standard deviations (SDs) above the county-month average as having extreme heat. This normalization enables us to identify extreme weather while accounting for long-term adaptation to historical temperature trends.[7] Appendix Table B.1 provides the average temperature cutoffs for our measure of extreme heat for each state and month combination.

Distribution of Temperature Exposure. Appendix Figure A.1(a) shows the distribution of prenatal exposure to daily average temperature using 10 temperature bins, and Appendix Figure A.1(b) depicts the distribution using 8 different SD bins. Five percent of observations in our data (124,431 and 132,704 maternal and infant records, respectively) have non-zero exposure to "above-3-SD heat".

Summary Statistics. Panel A of Appendix Table B.2 shows the average number of days per year with mean temperature falling in bins specified either in absolute (^oF ranges) or relative (SD ranges) terms in our three states. Arizona on average experiences 55 days per year with mean temperatures above 80^oF, but has zero days with above-3-SD heat. By contrast, New York and Washington, which have substantially fewer days with above 80^oF mean temperatures, have non-zero exposure to extreme heat. These differences underscore the importance of using a relative measure, rather than an absolute measure, to define exposure to extreme heat in each local area.

Panels B and C of Appendix Table B.2 provide means of some of the maternal and infant health outcomes that we analyze (expressed as rates per 100 mothers or infants). Approximately

[6] We have information on gestational age for only about 10 percent of our HCUP sample, which comes from diagnosis codes. It appears that gestational age is only recorded in cases where there are health complications, and we find that children with gestational age information have lower birth weight, longer length of stay, and higher likelihoods of readmission and death than those without gestational age information. Moreover, using actual pregnancy duration to assign exposure can be problematic due to the possible endogeneity of gestational age with respect to the *in utero* shock (Currie and Rossin-Slater, 2013).

[7] A growing literature demonstrates that accounting for adaptation is important for measuring the effects of temperature and climate change more broadly. In particular, individuals in historically hotter places may adapt to high temperatures through the adoption of mitigating technologies such as air conditioning and behavioral responses such as spending more time indoors. Consistent with this idea, several studies have documented geographic variation in the relationship between temperature and mortality (Deschênes and Greenstone, 2011; Barreca et al., 2015; 2016; Carleton et al., 2018).

four percent of women get hospitalized during pregnancy, with the most common diagnosis being a pregnancy-related complication. Overall, 0.5, 1.2, and 2.6 percent of women are hospitalized in the first, second, and third trimesters, respectively. Among infants, 0.03 percent are diagnosed with dehydration at birth, and 8.7 percent are readmitted to the hospital at some point post-birth observable in our data. Re-hospitalizations for jaundice, respiratory infections, and bronchitis are most common. There are some meaningful differences in the maternal and infant health outcomes across the three states, highlighting an additional reason for including state×year fixed effects in all our regression models, which we describe in more detail next.

3 Empirical Strategy

A robust medical literature highlights the biological mechanisms linking prenatal exposure to extreme heat with maternal and infant health (see Appendix C for more details), and the goal of this paper is to quantify this causal relationship. A central challenge is that exposure to hot days is not randomly assigned. For instance, several studies have documented differences in the health and human capital outcomes of children born in different months of the year due to selection into conception based on parental characteristics and differential exposure to seasonal factors such as the influenza virus (Buckles and Hungerman, 2013; Currie and Schwandt, 2013). In addition, there is non-random sorting of families into hotter and colder regions of the country based on incomes, preferences, and other characteristics, suggesting that cross-sectional comparisons between families residing in different regions are unlikely to isolate the causal effects of temperature exposure from the influences of other factors.

To address this challenge, we follow the prior literature by leveraging temperature variation *within* narrowly defined geographic and demographic cells, and flexibly accounting for local outcome trends. When studying maternal health, we collapse our data into cells defined by all possible combinations between the mother's county of residence at delivery, the year-month of childbirth, and race/ethnicity categories (White, Black, Hispanic, Asian American, and other). For infant outcomes, we collapse the data into birth-county×birth-year-month×race×sex cells.

We use the following regression model to estimate the effects of exposure to extreme temperature during pregnancy:

$$Y_{c,y,m,r,g} = \alpha + \sum_{t=1}^{3} \sum_{j=1, j\neq 5}^{8} \beta_{t,j} Temp_{c,y,m}^{t,j} + \sum_{t=1}^{3} \gamma_t f(Precip_{c,y,m}^{t}) + \theta_{c,m,r,g} + \eta_{y,s(c)} + \delta_{c,m} \times f(y) + \epsilon_{c,y,m,r,g} \tag{1}$$

for mothers residing in (or births in) county c, year y, month m, with mothers/infants of race/ethnicity r, and infants of sex g. $Y_{c,y,m,r,g}$ is an outcome, which we rescale by multiplying by 100 (e.g., the number of mothers admitted to the hospital during pregnancy per 100 mothers giving birth). The variables $Temp_{c,y,m}^{t,j}$ represent the number of days in each trimester t falling into each (j) of the eight bins of standard deviations of temperature from the county-month average, ranging from less than -3 SDs to at least 3 SDs or more, as illustrated in Appendix Figure A.1(b). The bin representing temperatures in the [0,1) SD range is omitted as the reference group. Thus, the $\beta_{t,j}$ coefficients can be interpreted as estimates of the impact of an additional day in a given temperature range (j) relative to a day in the [0,1) SD range in trimester t. We are particularly interested in the coefficient $\beta_{t,8}$, which measures the effect of an additional above-3-SD day in each trimester t.

We control for a third-order polynomial of mean precipitation in each trimester, $f(Precip_{c,y,m}^{t})$. $\theta_{c,m,r,g}$ are fixed effects for every birth-county×birth-month×race×sex cell. $\eta_{y,s(c)}$ are birth-state×birth-year fixed effects, which account for differential outcome trends across states, any state time-varying policies, and the fact that we observe states in different sets of years in the HCUP data. $\delta_{c,m} \times f(y)$ are county-by-calendar-month-specific trends (e.g., Queens-County-by-January-specific trends), which we model with a quadratic polynomial. We also control for the average number of mothers (or infants) per 100, residing in zip codes in different quartiles of the median income distribution. We weight all regressions by cell size, and cluster standard errors on the county level.[8]

Our model identifies the effects of extreme heat exposure using year-to-year deviations in temperature from the county-month trend within each cell. As a concrete example, consider a black woman giving birth in Queens county, New York, in August 2010 and a black woman giving birth in the same county in August 2011. Our empirical strategy leverages the arguably exogenous difference between them in the temperature deviation during their pregnancies from the Queens-specific quadratic trend among all August births, while controlling for the average difference in temperature exposure between all New York state births in 2010 and 2011.

A potential concern for our empirical design stems from the possibility that there is insufficient variation in temperature exposure left once we condition on all of the fixed effects and trends just described. In Appendix Figure A.2, we plot a histogram of the residuals from a regression of the number of days of *in utero* exposure to above-3-SD heat on the birth-county×birth-month×race×sex fixed effects, birth-state×birth-year fixed effects, and county×calendar-month-specific quadratic trends. The figure provides reassurance that there is enough variation left in the top temperature bin to estimate the effects of extreme heat shocks. In addition, as expected, there is more residual variation in extreme temperatures than in more typical temperatures (we depict the residual variation in exposure to less extreme temperature in Appendix Figure A.3).

Identifying Assumption. Our estimates of $\beta_{t,j}$ represent causal effects of prenatal exposure to temperature under the assumption that the within-cell variation in temperature (conditional on birth-state×birth-year fixed effects and county×calendar-month trends) is uncorrelated with other determinants of maternal and infant health. While this assumption is inherently untestable, we

[8] Results based on collapsed data with cell size weights are identical to those using the underlying individual-level data, since we do not have any other individual-level controls.

present some indirect tests to assess its plausibility.

First, we check whether there is any systematic relationship between our temperature variation and population demographic characteristics. We collapse our data to the birth-county×birth-year×birth-month level, and estimate a version of equation (1), excluding controls for demographic characteristics and zip code income quartiles. For outcomes, we consider the number of mothers (or infants) who are of different races/ethnicities, the number of female infants, and the numbers of mothers (or infants) residing in zip codes in different quartiles of the median income distribution per 100.

Appendix Table B.3 shows that our measure of extreme heat exposure is not correlated with either maternal or infant race, or infant sex.[9] In Appendix Table B.4, we find some evidence of a negative correlation between first trimester heat and the share of infants residing in zip codes in the bottom quartile of the median income distribution and between extreme heat in the third trimester and infants residing in zip codes in the top quartile of the median income distribution. However, we do not observe any significant relationship between exposure to heat in the second trimester and income, which is the time period of exposure for which we find the strongest effects on infant health. Nevertheless, to address the concern that differential trends in exposure to heat are correlated with income, we include controls for zip code level income quartiles in all of our regression models.

Second, we test the robustness of our results to including hypothetical exposure to temperature assuming a child was born two years prior to his/her actual birth year-month. As we show below, we do not detect any placebo effects on outcomes from two-year leads in temperature exposure, while our main effects of exposure during pregnancy remain strong and significant. Third, we show below that our estimates for infant health post-birth are robust to controlling for contemporaneous temperature exposure.

4 Results

4.1 Maternal Health

Table 1 and Figure 1 show that extreme heat exposure during second and third trimesters raises the likelihood of hospitalization during pregnancy.[10] Specifically, we find that an additional day with above-3-SD heat during the second (third) trimester raises the likelihood that a woman is hospitalized during pregnancy by 0.19 (0.12) percentage points. These coefficients translate into

[9]The lack of relationship between extreme heat exposure and infant sex also suggests that there is no effect on miscarriages, as changes in the sex ratio at birth are often used as proxies for changes in miscarriage rates (e.g., Sanders and Stoecker, 2015; Halla and Zweimüller, 2013).

[10]For ease of exposition, we summarize the estimates on exposure to days within each of the eight SD bins graphically, and present the regression estimates and standard errors on coefficients for exposure to above-3-SD heat in table format.

4.8 and 3.0 percent effect sizes, respectively, when evaluated at the sample means.

Table 1 further demonstrates that the increase in maternal hospitalizations is driven by hospitalizations due to pregnancy complications (ICD-9 codes 640-649).[11] We have also explored the timing of these hospitalizations, finding that second trimester heat exposure is associated with hospitalizations in both second and third trimesters (Appendix Table B.5). These results suggest that extreme heat has both immediate and persistent impacts on maternal pregnancy complications.

Further, we find differences in effects on prenatal hospitalization between black and white mothers.[12] Table 2 shows that the estimated adverse effect of extreme heat is much larger for black mothers than for white mothers, in both absolute and relative terms. For black mothers, we observe that an additional day of extreme heat during pregnancy increases the likelihood of hospitalization by 0.3 percentage points, or 5.0 percent at the sample mean. For white mothers, we find a 0.1 percentage point increase in the likelihood of prenatal hospitalization, which is 2.6 percent at the sample mean. While the difference in coefficients is not statistically significant at conventional levels (p-value is 0.14), these results nevertheless suggest that temperature exposure may be an important determinant of the widely documented black-white gap in maternal pregnancy-related health. In particular, as black mothers are on average exposed to more days with extreme heat than white mothers, our estimates imply that disparities in both the levels of extreme heat exposure and the magnitudes of the effects of exposure could help explain the racial gap in maternal health.

Appendix Table B.6 presents results for maternal health outcomes measured at childbirth. We find that exposure to an additional day with above-3-SD heat in the first trimester is associated with a 0.47 percentage point increase in the probability of having any complication related to pregnancy at childbirth (1.0 percent at the sample mean). We also find that an additional day of extreme heat during the third trimester increases the likelihood of a hypertension diagnosis at childbirth by 0.2 percentage points, or 2.9 percent. An increased risk of hypertension is supported by the medical literature on biological mechanisms of heat exposure (see Appendix C). Moreover, the higher incidence of complications at childbirth appears to increase maternal length of hospital stay. The last column of Appendix Table B.6 shows that an additional day with above-3-SD heat in the third trimester leads to a marginally significant 0.009 day increase in the average length of stay (0.3 percent). In supplementary analyses, we have also explored differences in effects on maternal health at childbirth by race. While the magnitude of the effect on length of stay appears to be larger for black than for white mothers, the estimates are imprecise, and we cannot rule out that the effect sizes are the same across the two groups (results available upon request).

In sum, our findings underscore that extreme heat exposure during pregnancy can generate

[11] More specifically, these include hospitalizations due to edema, excessive weight gain, renal disease, peripheral neuritis, asymptomatic bacteriuria, infections of genitourinary tract, and liver disorders (ICD 646); diabetes, thyroid dysfunction, anemia, and cardiovascular disorders (ICD 648); or tobacco use, obesity, coagulation defects, epilepsy, spotting, uterine size date discrepancy, and cervical shortening (ICD 649).

[12] When we estimate our models separately for black and white mothers, we drop counties that have fewer than 50 black or white mothers. This sample restriction allows us to identify the effects for each subgroup by providing sufficient variation in temperature exposure conditional on a large set of fixed effects and trends.

significant costs for maternal health, and that at least some of these health costs appear to be larger for black than for white mothers.

4.2 Infant Health

Having shown that prenatal exposure to extreme heat influences maternal health, we proceed to examine the effect of fetal exposure to extreme temperatures on infants.

Column (1) of Table 3 shows that an additional day of exposure to above-3-SD heat increases the likelihood that a newborn is diagnosed with dehydration by 0.008 percentage points (a 31 percent effect at the sample mean). This effect is driven by exposure to extreme heat during the second trimester (Appendix Figure A.4(a)-(c)).

The increase in dehydration is relevant in light of the fact that dehydration is one of the leading causes of morbidity and mortality in children (King et al., 2003; Black et al., 2003; Steiner et al., 2004). A number of medical studies document that children under five years old have an average of two episodes of gastroenteritis associated with dehydration per year, leading to 2 to 3 million pediatric office visits and accounting for 10 percent of all pediatric hospital admissions in the U.S. (King et al., 2003; McConnochie et al, 1999; Glass et al, 1991). Thus, an increased incidence of dehydration at birth may lead to increased future hospitalizations among children.

Consistent with this conjecture, column (2) of Table 3 and Appendix Figure A.4(d)-(f) show that an additional day of exposure to above-3-SD heat in the second trimester raises the likelihood of infant readmission to the hospital by 0.3 percentage points (3.4 percent). When we explore the timing of readmission in Appendix Table B.7, it appears that the effect is concentrated between the age of 100 days and one year.[13]

In Table 4, we examine the diagnosis codes at the time of readmission. We find that exposure to second trimester heat is associated with re-hospitalization due to prenatal jaundice, prenatal hematological disorders, and respiratory conditions including bronchitis, influenza, and pneumonia. Combining with our results on dehydration at birth, the results on re-hospitalizations with these diagnoses are consistent with a medical literature on the link between dehydration and later childhood diseases, including bronchitis and bacterial infections such as pneumonia (e.g., Steiner et al., 2004; Green et al., 2010).

Overall, our findings on infant health suggest that exposure to extreme heat during the second trimester increases the likelihood of the baby being dehydrated at the time of birth. This, in turn, appears to increase the likelihood of subsequent readmission to the hospital many months later for causes linked to dehydration. Importantly, these impacts are missed when one only measures

[13] While we are not aware of any medical studies directly linking dehydration at birth with the timing of subsequent hospitalization, the delayed effect on hospitalization is consistent with other evidence that the temperature-induced risk of Sudden Infant Death Syndrome (SIDS) is greater for children between 3 and 12 months of age than for infants under 3 months (Auger et al., 2017).

infant health using more standard variables, such as birth weight.[14]

4.3 Additional Results

Placebo Temperature Exposure. To assess the possibility of bias due to differential trends in temperature exposure that are not controlled for in our main regression models, we test the robustness of our results to including two-year leads of temperature exposure. In particular, for every birth-county×birth-year-month, we calculate the hypothetical exposure to temperature assuming that the child had been born two years prior. We use a two-year (instead of a one-year) lead to avoid confounding our estimates with possible effects of temperature on conception or fertility (Lam et al., 1994; Barreca et al., 2015; Wilde et al., 2017). Appendix Table B.8 shows that our results are robust to the inclusion of this control.

Controlling for Contemporaneous Temperature Exposure. We next examine whether our results on children's post-birth outcomes are sensitive to controlling for contemporaneous temperature exposure.[15] White (2017) finds that exposure to cold and hot temperatures has significant effects on immediate hospitalizations on the same day as well as hospitalizations in the following 30 days. If contemporaneous temperature is correlated with *in utero* temperature exposure in a way not accounted for by our controls, then there may be bias in our estimated effects.

To control for contemporaneous temperature, we use two approaches: (1) we control for the number of days in each of the eight SD temperature bins in the child's first year of life, and (2) we control for the average number of days in each of the eight SD temperature bins over all observable years of the child's life. Note we measure contemporaneous temperature assuming that the child's county of birth is his/her county of residence in the future and regardless of whether the child is re-hospitalized or not. Appendix Table B.9 indicates that the effect of extreme heat in the second trimester remains statistically significant for most outcomes.

Absolute Temperature Exposure. Lastly, we examine whether our results are robust to using absolute temperature instead of our relative measure based on deviations from each county's overall average temperature. We find that the main results presented above are mostly driven by mothers and infants from New York state (Appendix Table B.10). Thus, we repeat our analysis using absolute temperature exposure for the sub-sample of New York mothers and infants. Appendix Table B.11 shows that our findings are robust to using absolute temperature measures. We find similar effects of an additional day above 90 degrees on maternal prenatal hospitalization as well

[14]We have examined more commonly studied infant health outcomes, including birth weight, length of hospital stay, and in-hospital death, finding null effects. We have also explored heterogeneity in effects of extreme heat on infant health by race, finding no evidence of significant differences. All results available upon request.

[15]Note that our results on mothers' health at childbirth already control for contemporaneous temperature exposure as we assume that the month of birth is the last month of the third trimester (during which we measure temperature exposure in our main models).

as infant dehydration and readmission. Appendix Figure A.5 consistently shows that prenatal hospitalization increases in response to above-90-degree heat during the second and third trimesters.

5 Conclusion

Scientists predict that global average temperatures will rise over the next 50 to 100 years, mostly due to a shift to the right in the upper tail of the temperature distribution. For instance, the number of days with mean temperature above 32°C in the average American county is forecasted to increase from about 1 to approximately 43 per year by 2070-2099 (Intergovernmental Panel on Climate Change, 2014). Understanding the health consequences of this increase in extreme heat is critical for informing discussions about the costs of climate change and the possible benefits of mitigating policies. Moreover, a growing literature demonstrates heterogeneity in effects of heat across regions with different average temperatures and the importance of adaptation (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Barreca et al., 2015; Barreca et al., 2016; Carleton et al., 2018), suggesting that extreme *deviations* from typical weather may be particularly damaging.

In this paper, we contribute to the evidence on the costs of exposure to extreme heat by documenting maternal and infant health impacts. We use the universe of inpatient discharge records from three states and find that exposure to extreme heat in the second trimester of pregnancy—which we measure using standard deviations relative to each county's overall monthly temperature mean—leads to an increase in women's hospitalizations for pregnancy-related complications. We find that prenatal exposure to extreme heat raises the likelihood that a mother is diagnosed with hypertension at childbirth, and slightly increases her length of hospital stay. The fact that the adverse impacts on health during pregnancy are larger for black than for white mothers suggests that climate change may exacerbate the already large racial gap in maternal health.

We also find that *in utero* exposure to extreme heat increases the risk of a newborn being diagnosed with dehydration and an infant being re-hospitalized in the first year of life for causes linked to dehydration. Thus, our results shed light on a potential mechanism behind the previously documented relationship between early-life temperature exposure and long-term outcomes—early childhood health complications associated with dehydration may inhibit children's ability to learn and develop skills that influence future human capital formation.

An important limitation of our study is that we are not able to measure health impacts not captured by the hospitalizations data. Just like standard measures of infant health (like birth weight) may miss more nuanced effects on other aspects of health that we *do* measure, our estimates based on hospitalizations cannot capture potential impacts on more minor health insults that do not lead to hospital encounters. Future research may expand our understanding of these effects with better data on other health conditions.

References

Almond, D. and J. Currie (2011a). Human Capital Development before Age Five. *Handbook of Labor Economics*

Almond, D. and J. Currie (2011b). Killing Me Softly: The Fetal Origins Hypothesis. *Journal of Economic Perspectives* 25(3), 153–172

Almond, D., J. Currie, and V. Duque (2018). Childhood Circumstances and Adult Outcomes: Act II. *Journal of Economic Literature* 56(4), 1360–1446

Astrand, P. O., et al. (2003). Textbook of Work Physiology: Physiological Bases of Exercise, 4th ed. McGraw-Hill, Canada.

Auger, N., W. D. Fraser, A. Smargiassi, M. Bilodeau-Bertrand, and T. Kotasky (2017). Elevated Outdoor Temperatures and Risk of Stillbirth. *Int. J. Epidemiol* 46(1), 200–208

Barker, D. J. (1990). The Fetal and Infant Origins of Adult Disease. *The BMJ* 301(6761), 1111

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. Shapiro (2015). Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 19002004. *American Economic Review: Papers & Proceedings* 105(5), 247–251

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. Shapiro (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy* 124(1),105–159

Barreca, A., O. Deschenes, and M. Guldi (2018). Maybe Next Month? Temperature Shocks and Dynamic Adjustments in Birth Rates. *Demography* 55(4), 1269–1293

Beltran, A., J. Wu, and O. Laurent (2014). Associations of Meteorology with Adverse Pregnancy Outcomes: a Systematic Review of Preeclampsia, Preterm Birth and Birth Weight. *Chronic Dis. Can.* 11, 91–172

Black, S. E., P. J. Devereux, and K. Salvanes (2007). From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes *The Quarterly Journal of Economics* 122(1), 409–439

Black, R. E., S. S. Morris, and J. Bryce (2003). Where and Why are 10 million Children Dying Every Year? *Lancet* 361, 2226–2234

Buckles, K. and D. Hungerman (2013). Season of Birth and Later Outcomes: Old Questions, New Answers. *Review of Economics and Statistics* 95(3), 711–724

Carleton, T., M. Delgado, M. Greenstone, T. Houser, S. Hsiang, A. Hultgren, A. Jina, R. Kopp, K. McCusker, I. Nath, J. Rising, A. Rode, H. Seo, J. Simcock, A. Viaene, J. Yuan, and A. Zhang (2018). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits. University of Chicago, Becker Friedman Institute for Economics

Working Paper No. 2018-51.

Cho, H. (2017). Effect of Summer Heat on Test Scores: A Cohort Analysis. *Journal of Environmental Economics and Management* 83, 185–196

Conti, G., M. Hanson, H. Inskip, S. Crozier, C. Cooper, and K. Godfrey (2018). Beyond Birth Weight: The Origins of Human Capital. Working Papers 2018-089, Human Capital and Economic Opportunity Working Group.

Cunha, F. and J. Heckman (2007). The Technology of Skill Formation. *American Economic Review* 97(2), 31–47

Currie, J. and M. Rossin-Slater (2013). Weathering the Storm: Hurricanes and Birth Outcomes. *Journal of Health Economics* 32, 487–503

Currie, J. and H. Schwandt (2013). Within-mother Analysis of Seasonal Patterns in Health at Birth. *PNAS* 110(30), 12265–12270

Dadvand, P., X. Basagana, and C. Sartini (2011). Climate Extremes and the Length of Gestation *Environ. Health Perspect.* 119 (10), 1449–1453

Deschenes, O., M. Greenstone, and J. Guryan (2009). Climate Change and Birth Weight. *American Economic Review* 99(2), 211–217

Deschenes, O., and M. Greenstone (2011). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. *American Economic Journal: Applied Economics* 3, 152–185

Deschenes, O., and E. Moretti (2009). Extreme Weather Events, Mortality, and Migration. *The Review of Economics and Statistics* 91(4), 659–681

Garg, T., M. Jagnani, and V. Taraz (2018). Temperature and Human Capital in India. Available at SSRN: https://ssrn.com/abstract=2941049 or http://dx.doi.org/10.2139/ssrn.2941049

Glass, R. I., J. F. Lew, R. E. Gangarosa, C. W. LeBaron, and M. S. Ho (1991). Estimates of Morbidity and Mortality Rates for Diarrheal Diseases in American Children. *J Pediatr* 118(4 pt 2), S27–S33

Goodman, J., M. Hurwitz, J. Park, and J. Smith (2018). Heat and Learning. NBER Working Paper No. 24639

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labor Economics* 32(1), 1–26

Graff Zivin, J., S. M. Hsiang, and M. Neidell (2018). Temperature and Human Capital in the Short and Long Run. *Journal of the Association of Environmental and Resource Economists* 5(1), 77–105

Green, R., R. Basu, B. Malig, R. Broadwin, J. Kim, and B. Ostro (2010). The Effect of Temperature on Hospital Admissions in Nine California Counties. *Int. J. Public Health* 55, 113–121

Gronlund, C. J. (2014). Racial and Socioeconomic Disparities in Heat-Related Health Effects and Their Mechanisms: a Review. *Current Epidemiology Reports* 1(3), 165–173

Ha, S., D. Liu, Y. Zhu, S. Kim, S. Sherman, K. Grantz, and P. Mendola (2017). Ambient Temperature and Stillbirth: a Multi-center Retrospective Cohort Study. *Environ. Health Perspect.* 125, Article 067011

Ha, S., D. Liu, Y. Zhu, S. Kim, S. Sherman, and P. Mendola (2017). Ambient Temperature and Early Delivery of Singleton Pregnancies. *Environ. Health Perspect.* 125, 453–459

Halla, Martin, and Martina Zweimüller (2013). Parental Response to Early Human Capital Shocks: Evidence from the Chernobyl Accident. *IZA Discussion Paper* 7968.

He, S., T. Kosatsky, A. Smargiassi, M. Bilodeau-Bertrand, and N. Auger (2018). Heat and Pregnancy-related Emergencies: Risk of Placental Abruption During Hot Weather. *Environment International* 111, 295–300

Heckman, J., and S. Mosso (2014). The Economics of Human Development and Social Mobility. *Annual Review of Economics* 6(1), 689–733

Hu, Z., and T. Li (2019). Too Hot to Handle: The Effects of High Temperatures During Pregnancy on Adult Welfare Outcomes. *Journal of Environmental Economics and Management* 94, 236–253

Intergovernmental Panel on Climate Change (2014). Climate Change 2014: Synthesis Report.

Isen, A., M. Rossin-Slater, and R. Walker (2017). Relationship Between Seasons of Birth, Temperature Exposure, and Later Life Wellbeing. *PNAS* 114(51), 13447–13452

Kassebaum, N. J., R. M. Barber, Z. A. Bhutta, L. Dandona, P. W. Gething, S. I. Hay, Y. Kinfu, H. J. Larson, X. Liang, and S. S. Lim (2016). Global, Regional, and National Levels of Maternal Mortality, 1990–2015: A Systematic Analysis for the Global Burden of Disease Study 2015. *The Lancet* 388 (10053), 17751812.

King, C.K., R. Glass, J. S. Bresce, and C. Duggan (2003). Managing Acute Gastroenteritis among Children. *MMWR Recommendations and Reports* 52(16), 1–16

King, J. (2004). Thermoregulation: Physiological Responses and Adaptations to Exercise in Hot and Cold Environments. *J. Hyperplasia Res* 4.

Knobel, R. and D. Holditch-Davis (2007). Thermoregulation and Heat Loss Prevention after Birth and During Neonatal Intensive-care Unit Stabilization of Extremely Low-Birthweight Infants. *Journal of Obstetric, Gynecologic, and Neonatal Nursing* 36, 280–287.

Kuehn, L., and S. McCormick (2017). Heat Exposure and Maternal Health in the Face of Climate Change. *International Journal of Environmental Research and Public Health* 14(8): 853.

Lam, D. A., J. A. Miron, and A. Riley (1996). The Effects of Temperature on Human Fertility. *Demography* 33(3), 291–305

McConnochie, K. M., G. P. Conners, E. Lu, and C. Wilson (1999). How Commonly are Children Hospitalized for Dehydration Eligible for Care in Alternative Settings? *Arch Pediatr Adolesc Med* 153, 1233–1241

NASA (2013). More Extreme Weather Events Forecast. `https://www.nasa.gov/centers/langley/science/climate_assessment_2012.html`

O'Neill, M. S., Zanobetti, A., and Schwartz, J. (2005). Disparities by Race in Heat-related Mortality in Four US Cities: the Role of Air Conditioning Prevalence. *Journal of Urban Health*, 82(2), 191-197.

Petersen, E. E., Davis, N. L., Goodman, D., Cox, S., Mayes, N., Johnston, E., Syverson, C., Seed, K., Shapiro-Mendoza, C.K., Callaghan, W.M. and Barfield, W. (2019). Vital Signs: Pregnancy-Related Deaths, United States, 2011–2015, and Strategies for Prevention, 13 States, 2013–2017. *Morbidity and Mortality Weekly Report*, 68(18), 423–429.

Royer, H. (2009). Separated at Girth: US Twin Estimates of the Effects of Birth Weight. *American Economic Journal: Applied Economics* 1(1), 49–85

Sanders, Nicholas J., and Charles Stoecker (2015). Where Have All the Young Men Gone? Using Sex Ratios to Measure Fetal Death Rates. *Journal of Health Economics* 41: 30–45.

Schifano, P., F. Asta, P. Dadvand, M. Davoli, X. Basagana, and P. Michelozzi (2016). Heat and Air Pollution Exposure as Triggers of Delivery: a Survival Analysis of Population-based Pregnancy Cohorts in Rome and Barcelona. *Environment International* 88, 153–159

Steiner, M. J., D.A. DeWalt, and J. S. Byerley (2004). Is This Child Dehydrated? *JAMA* 291(22), 2746–2754.

Veha-Eskeli, K., and R. Erkkola (1991). The Effect of Short-term Heat Stress on Uterine Contractility, Fetal Heart Rate and Fetal Movements at Late Pregnancy. *Eur. J. Obstet. Gynecol. Reprod. Biol.* 38, 9–14

White, C. (2017). The Dynamic Relationship Between Temperature and Morbidity. *Journal of the Association of Environmental and Resource Economists* 4(4), 1155–1198

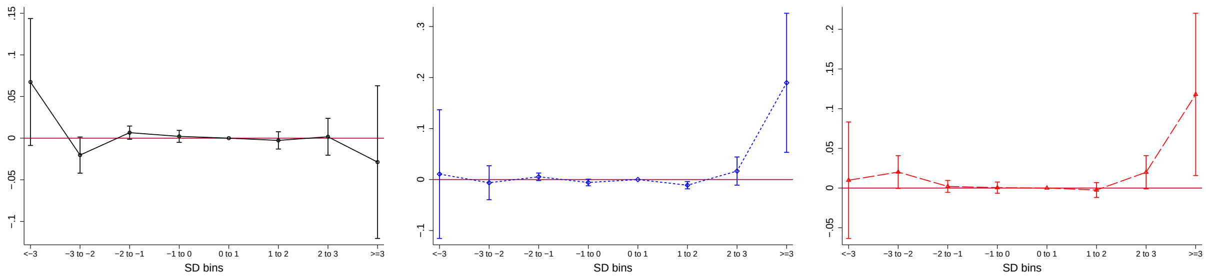
Wilde, A., B. H. Apouey, and T. Jung (2017). The Effect of Ambient Temperature Shocks during Conception and Early Pregnancy on Later Life Outcomes. *European Economic Review* 97(C), 87–107

Xu, Z., R. A. Etzel, H. Su, C. Huang, Y. Guo, and S. Tong (2012). Impact of Ambient Temperature on Children's Health: A Systematic Review. *Environmental Research* 117, 120–131

Yackerson, N. S., B. Piura, and M. Friger (2007). The Influence of Weather State on the Incidence of Preeclampsia and Placental Abruption in Semi-arid Areas. *Clin. Exp. Obstet. Gynecol.* 34, 27–30

Young, J. B. (2002). Programming of Sympathoadrenal Function. *Trends Endocrinol Metab* 13, 381–385

6 Figures



(a) Hospitalization during pregnancy, trimester 1 exposure

(b) Hospitalization during pregnancy, trimester 2 exposure

(c) Hospitalization during pregnancy, trimester 3 exposure

Figure 1: **Effects of Temperature During Pregnancy on Prenatal Hospitalization**

Notes: The figures plot regression coefficients, $\beta_{t,j}$, from equation (1) for each SD bin (j) for each trimester (t) with 95% confidence intervals. Outcome is rescaled by multiplying by 100. Standard errors are clustered at the birth county level. All regressions control for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

7 Tables

Table 1: Effects of Exposure to Above-3-SD Heat on Prenatal Hospitalization

	(1)	(2)	(3)	(4)	(5)
	Prenatal hospitalization	Diagnoses associated with prenatal hospitalization			
		ICD 640-649	ICD 646	ICD 648	ICD 649
# Days above-3-SD heat in trimester 1	-0.029	-0.029	0.035	-0.026	0.000
	(0.046)	(0.050)	(0.023)	(0.034)	(0.017)
# Days above-3-SD heat in trimester 2	0.190***	0.167**	0.045*	0.089**	0.026
	(0.069)	(0.067)	(0.026)	(0.041)	(0.021)
# Days above-3-SD heat in trimester 3	0.118**	0.137***	0.053**	0.112***	0.029
	(0.052)	(0.046)	(0.023)	(0.036)	(0.021)
Observations	44342	44342	44342	44342	44342
Adjusted R^2	0.466	0.455	0.162	0.351	0.146
Mean	3.995	3.722	0.869	2.031	0.273

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used. ICD codes 640-649 indicate "complications mainly related to pregnancy." ICD 646 is for "other complications of pregnancy, not elsewhere classified," which includes edema, excessive weight gain, renal disease, peripheral neuritis, asymptomatic bacteria, infections of genitourinary tract, and liver disorders. ICD 648 indicates "other current conditions in the mother classifiable elsewhere," such as diabetes, thyroid dysfunction, anemia, and cardiovascular disorders. ICD 649 is for "other conditions or status of the mother complicating pregnancy, childbirth, or the puerperium," including tobacco use, obesity, coagulation defects, epilepsy, spotting, uterine size date discrepancy, and cervical shortening. * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Effects of Exposure to Above-3-SD Heat on Prenatal Hospitalization by Race

	(1)	(2)	(3)	(4)	(5)
	Prenatal hospitalization	Diagnoses associated with prenatal hospitalization			
		ICD 640-649	ICD 646	ICD 648	ICD 649
Panel A. White mothers					
# Days above-3-SD heat during pregnancy	0.100**	0.100**	0.054**	0.057**	0.026**
	(0.040)	(0.044)	(0.026)	(0.027)	(0.012)
Observations	9835	9835	9835	9835	9835
Adjusted R^2	0.449	0.433	0.137	0.308	0.149
Mean	3.873	3.619	0.880	1.925	0.303
Panel B. Black mothers					
# Days above-3-SD heat during pregnancy	0.299**	0.308*	0.124**	0.072	0.058
	(0.139)	(0.154)	(0.061)	(0.099)	(0.051)
Observations	4923	4923	4923	4923	4923
Adjusted R^2	0.449	0.427	0.170	0.302	0.298
Mean	6.135	5.784	1.109	3.508	0.464
P-value from testing the difference	0.136	0.153	0.318	0.883	0.516

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1), where t combines all three semesters. We drop counties that have fewer than 50 black or white mothers for this subgroup analysis. Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used. ICD codes 640-649 indicate "complications mainly related to pregnancy." ICD 646 is for "other complications of pregnancy, not elsewhere classified," which includes edema, excessive weight gain, renal disease, peripheral neuritis, asymptomatic bacteriuria, infections of genitourinary tract, and liver disorders. ICD 648 indicates "other current conditions in the mother classifiable elsewhere," such as diabetes, thyroid dysfunction, anemia, and cardiovascular disorders. ICD 649 is for "other conditions or status of the mother complicating pregnancy, childbirth, or the puerperium," including tobacco use, obesity, coagulation defects, epilepsy, spotting, uterine size date discrepancy, and cervical shortening. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Effects of Exposure to Above-3-SD Heat on Infant Health

	(1)	(2)
	Dehydration at birth	Readmission
# Days above-3-SD heat in trimester 1	-0.002	0.114
	(0.004)	(0.107)
# Days above-3-SD heat in trimester 2	0.008*	0.299**
	(0.004)	(0.143)
# Days above-3-SD heat in trimester 3	0.002	0.146
	(0.004)	(0.194)
Observations	75328	75328
Adjusted R^2	0.017	0.651
Mean	0.026	8.686

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for infant's race×infant's sex×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Effects of Exposure to Above-3-SD Heat on Diagnoses at Infant Hospital Readmission

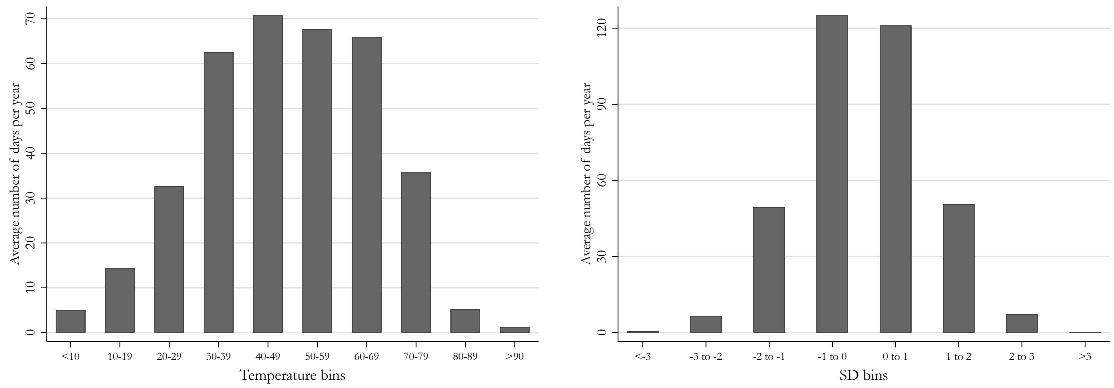
	(1) Jaundice	(2) Hematological disorder	(3) Respiratory infection	(4) Bronchitis	(5) Influenza	(6) Pneumonia
# Days above-3-SD heat in trimester 1	0.067***	0.006	0.040	0.033	0.036	0.035**
	(0.021)	(0.006)	(0.040)	(0.031)	(0.024)	(0.017)
# Days above-3-SD heat in trimester 2	0.023	0.009*	0.066	0.059*	0.055*	0.041
	(0.025)	(0.005)	(0.041)	(0.032)	(0.030)	(0.028)
# Days above-3-SD heat in trimester 3	-0.006	-0.001	-0.041	-0.045	0.004	0.005
	(0.040)	(0.006)	(0.056)	(0.044)	(0.038)	(0.022)
Observations	75328	75328	75328	75328	75328	75328
Adjusted R^2	0.332	-0.018	0.269	0.232	0.136	0.092
Mean	1.574	0.092	1.726	1.321	0.970	0.660

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for infant's race×infant's sex×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Online Appendix

Appendix A. Appendix Figures



(a) Using 10 temperature bins

(b) Using 8 SD bins

Figure A.1: Distributions of Daily Average Temperature

Sources: NOAA weather data.

Notes: Daily average temperature is obtained by taking average of minimum and maximum temperature in a given day measured at weather stations in Arizona 2003 to 2007, New York 2003 to 2013, and Washington 2003 to 2013.

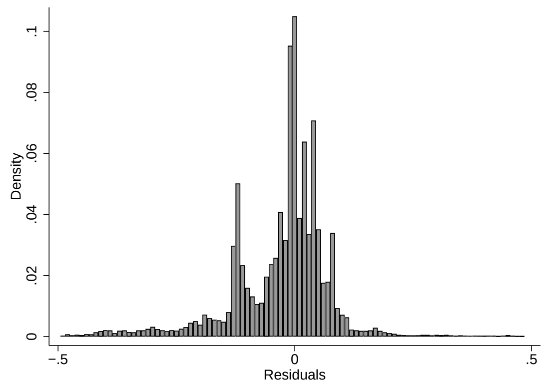
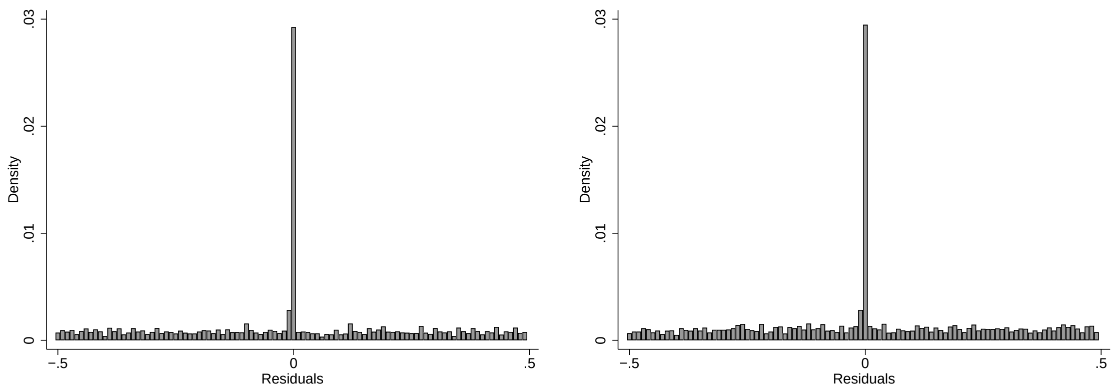


Figure A.2: Histogram of the Distribution of the Residuals in Extreme Temperature After Conditioning on All Fixed Effects and Trends

Notes: We compute residuals from a regression of the raw number of days with temperature above 3 SDs during a three-month period on race×sex×birth-county×birth-month fixed effects and birth-state×birth-year fixed effects and county×calendar month-specific quadratic trends. The distribution shows 1.5 SD deviations below and above the mean residuals. We use the data collapsed at the race×sex×birth-county×birth-year-month level.

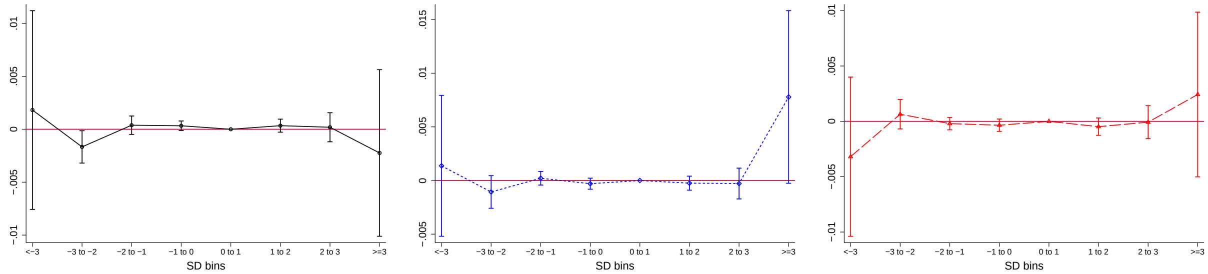


(a) -1 to 0 SD temperature exposure

(b) 1 to 2 SD temperature exposure

Figure A.3: Histogram of the Distribution of the Residuals After Conditioning on All Fixed Effects and Trends

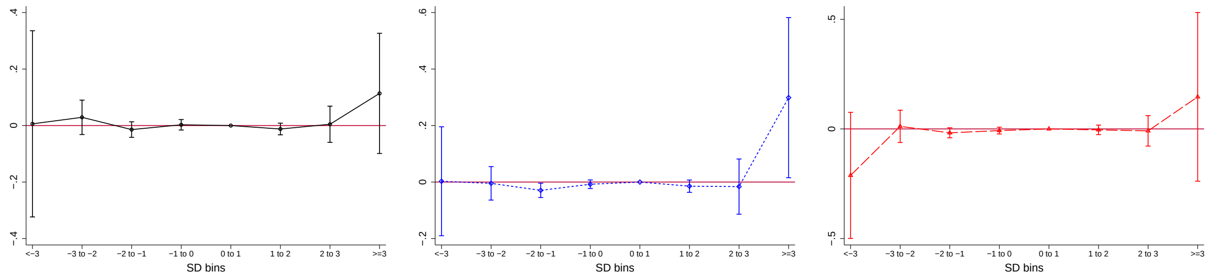
Notes: Panel (a) plots the residuals from a regression of the raw number of days with temperature between -1 and 0 SD during a three-month period on race×sex×birth-county×birth-month fixed effects and birth-state×birth-year fixed effects and county×calendar month-specific quadratic trends. Panel (b) plots the residuals from a regression of the raw number of days with temperature between 1 and 2 SD during a three-month period on race×sex×birth-county×birth-month fixed effects and birth state×birth-year fixed effects and county×calendar month-specific quadratic trends. Each distribution shows residuals ranging from -0.5 to 0.5. We use the data collapsed at the race×sex×birth-county×birth-year-month level.



(a) Dehydration, trimester 1 exposure

(b) Dehydration, trimester 2 exposure

(c) Dehydration, trimester 3 exposure



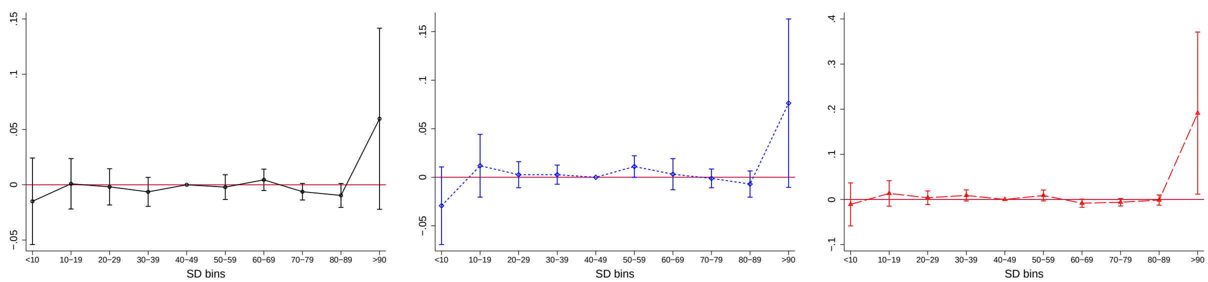
(d) Readmission, trimester 1 exposure

(e) Readmission, trimester 2 exposure

(f) Readmission, trimester 3 exposure

Figure A.4: Effects of In Utero Temperature on Infant Health

Notes: The figures plot regression coefficients, $\beta_{t,j}$, from equation (1) for each SD bin (j) for each trimester (t) with 95% confidence intervals. Outcome is rescaled by multiplying by 100. Standard errors are clustered at the birth county level. All regressions control for infant's race/ethnicity×sex×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level. Cell size weights are used.



(a) Hospitalization during pregnancy, trimester 1 exposure

(b) Hospitalization during pregnancy, trimester 2 exposure

(c) Hospitalization during pregnancy, trimester 3 exposure

Figure A.5: Effects of Temperature During Pregnancy on Prenatal Hospitalization in New York

Notes: The figures plot regression coefficients, $\beta_{t,j}$, from equation (1) for each SD bin (j) for each trimester (t) with 95% confidence intervals. Each outcome is rescaled by multiplying by 100. Standard errors are clustered at the birth county level. All regressions control for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

Appendix B. Appendix Tables

Table B.1: Temperature Cutoffs for Extreme Heat Exposure (^oF)

	(1)	(2)	(3)
	Arizona	New York	Washington
A. Average cutoff for 2-SD above the county-month averages			
January	46.3	41.8	43.2
February	49.3	37.5	41
March	53.8	48.5	45.9
April	57.8	57	50.7
May	68.0	67.8	60.3
June	96.8	74.5	64.5
July	74.5	75.5	68
August	70.5	75.5	66.5
September	72.2	71	64.3
October	60.8	62.5	55
November	63.4	52	46.3
December	44.6	43.2	37.9
B. Average cutoff for 3-SD above the county-month averages			
January	.	56.1	52.1
February	.	.	.
March	.	61.7	53.7
April	.	67.5	58.4
May	.	80	65.4
June	.	.	69
July	.	84.1	71.8
August	.	83	70.3
September	.	82.5	68
October	.	.	65
November	.	.	.
December	.	56	52.5

Sources: NOAA weather data.
Notes: For each state, we calculate average temperature cutoffs for our measures of extreme heat, 2 or 3 standard deviations above the overall mean temperature for a given county and month. Arizona experiences no exposure to above-3-SD heat during our study period. New York and Washington also do not experience above-3-SD heat in some months.

Table B.2: Summary Statistics

	(1)	(2)	(3)	(4)
	Combining three states	Arizona	New York	Washington
A. Exposure to temperature extremes				
Annual days with mean temperature				
$[80^oF, 90^oF)$	5.206	38.907	3.324	1.612
$\geq 90^oF$	1.178	16.533	0.046	0.003
$[2, 3)$ SD	7.291	3.920	7.154	8.198
≥ 3 SD	0.303	0	0.183	0.567
B. Maternal health outcomes (per 100 mothers)				
Any hospitalization during pregnancy	3.995	3.645	4.032	4.022
Diagnosis at prenatal hospitalization				
Any complications (ICD 640-649)	3.722	3.501	3.771	3.659
- Other complications (ICD 646)	0.869	0.961	0.855	0.876
- Other current conditions (ICD 648)	2.031	1.778	2.129	1.837
- Other conditions (ICD 649)	0.273	0.032	0.279	0.351
Timing of prenatal hospitalization				
Trimester 1	0.546	0.279	0.606	0.468
Trimester 2	1.212	0.880	1.261	1.195
Trimester 3	2.562	2.685	2.505	2.683
Observations	44349	3902	30347	10100
C. Child health outcomes (per 100 children)				
Dehydration at birth	0.026	0.002	0.030	0.025
Any readmission post-birth	8.686	6.269	7.274	14.340
Diagnosis at readmission				
Jaundice	1.574	0.915	1.065	3.526
Hemotological disorder	0.092	0.054	0.053	0.234
Respiratory infection	1.726	1.405	1.593	2.292
Bronchitis	1.321	1.068	1.225	1.741
Influenza	0.970	1.000	0.888	1.232
Pneumonia	0.660	0.766	0.600	0.815
Observations	75339	6361	53013	15965

Sources: NOAA weather data and HCUP databases.

Notes: We use the data collapsed at the race×sex×birth-county×birth-year-month level. Temperature cutoffs for 2-SD and 3-SD above county-month averages are summarized by state in Appendix Table B.1. ICD codes 640-649 indicate "complications mainly related to pregnancy." ICD 646 is for "other complications of pregnancy, not elsewhere classified," which includes edema, excessive weight gain, renal disease, peripheral neuritis, asymptomatic bacteriuria, infections of genitourinary tract, and liver disorders. ICD 648 indicates "other current conditions in the mother classifiable elsewhere," such as diabetes, thyroid dysfunction, anemia, and cardiovascular disorders. ICD 649 is for "other conditions or status of the mother complicating pregnancy, childbirth, or the puerperium," including tobacco use, obesity, coagulation defects, epilepsy, spotting, uterine size date discrepancy, and cervical shortening.

Table B.3: Placebo Outcome: Race and Sex

	(1) White	(2) Black	(3) Hispanic	(4) Asian	(5) Native American	(6) Others	(7) Female
A. Maternal records							
# Days above-3-SD heat in trimester 1	0.343	-0.044	-0.316	-0.214	-0.062	0.292	
	(0.479)	(0.181)	(0.448)	(0.275)	(0.076)	(0.565)	
# Days above-3-SD heat in trimester 2	-0.274	0.127	-0.163	0.097	0.007	0.206	
	(0.566)	(0.118)	(0.326)	(0.320)	(0.054)	(0.370)	
# Days above-3-SD heat in trimester 3	-0.257	0.092	0.130	0.040	-0.034	0.029	
	(0.405)	(0.095)	(0.381)	(0.140)	(0.039)	(0.297)	
Observations	10122	10122	10122	10122	10122	10122	
Adjusted R^2	0.962	0.972	0.934	0.889	0.889	0.827	
Mean	76.614	4.547	11.286	2.305	1.967	3.281	
B. Infant records							
# Days above-3-SD heat in trimester 1	0.954	-0.124	-0.498	-0.441	-0.019	0.127	0.165
	(0.713)	(0.183)	(0.494)	(0.492)	(0.082)	(0.680)	(0.133)
# Days above-3-SD heat in trimester 2	0.099	0.026	-0.042	-0.162	0.022	0.057	-0.140
	(0.370)	(0.086)	(0.360)	(0.149)	(0.060)	(0.398)	(0.153)
# Days above-3-SD heat in trimester 3	-0.423	0.084	0.149	0.148	0.008	0.034	-0.034
	(0.443)	(0.085)	(0.306)	(0.214)	(0.060)	(0.306)	(0.127)
Observations	9877	9877	9877	9877	9877	9877	11741
Adjusted R^2	0.952	0.967	0.931	0.866	0.836	0.854	0.028
Mean	75.490	4.476	10.722	2.252	2.184	4.875	48.816

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. All regressions control for birth-county×birth-month fixed effects, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the birth-county×birth-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.4: Placebo Outcome: Zip Income Quartile

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
A. Maternal records				
# Days above-3-SD heat in trimester 1	-0.446	0.474	-0.017	-0.010
	(0.326)	(0.319)	(0.373)	(0.406)
# Days above-3-SD heat in trimester 2	0.036	0.242	-0.037	-0.241
	(0.414)	(0.349)	(0.354)	(0.342)
# Days above-3-SD heat in trimester 3	0.166	-0.127	0.317	-0.355
	(0.471)	(0.448)	(0.467)	(0.309)
Observations	8979	8979	8979	8979
Adjusted R^2	0.958	0.918	0.915	0.985
Mean	25.033	41.301	22.978	10.688
B. Infant records				
# Days above-3-SD heat in trimester 1	-0.635*	0.523	0.125	-0.013
	(0.343)	(0.319)	(0.387)	(0.422)
# Days above-3-SD heat in trimester 2	-0.036	0.293	0.077	-0.334
	(0.417)	(0.368)	(0.330)	(0.328)
# Days above-3-SD heat in trimester 3	0.130	-0.063	0.416	-0.483*
	(0.434)	(0.419)	(0.424)	(0.267)
Observations	8811	8811	8811	8811
Adjusted R^2	0.954	0.914	0.911	0.984
Mean	24.798	41.259	22.967	10.976

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. All regressions control for birth-county×birth-month fixed effects, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the birth-county×birth-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.5: Effects of Exposure to Above-3-SD Heat on the Timing of Prenatal Hospitalization

	(1) Trimester 1	(2) Trimester 2	(3) Trimester 3
# Days above-3-SD heat in trimester 1	-0.018	0.017	-0.020
	(0.014)	(0.029)	(0.048)
# Days above-3-SD heat in trimester 2	0.005	0.084***	0.133***
	(0.015)	(0.027)	(0.049)
# Days above-3-SD heat in trimester 3	0.025	0.084***	0.026
	(0.023)	(0.029)	(0.036)
Observations	44342	44342	44342
Adjusted R^2	0.225	0.327	0.324
Mean	0.546	1.212	2.562

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.6: Effects of Exposure to Above-3-SD Heat on Maternal Health at Childbirth

	(1)	(2)	(3)
	Any complication	Hypertension	Length of stay
# Days above-3-SD heat in trimester 1	0.474***	-0.016	0.007
	(0.165)	(0.083)	(0.006)
# Days above-3-SD heat in trimester 2	0.019	0.014	-0.001
	(0.189)	(0.066)	(0.006)
# Days above-3-SD heat in trimester 3	0.141	0.196**	0.009*
	(0.223)	(0.097)	(0.005)
Observations	44342	44342	44342
Adjusted R^2	0.554	0.286	0.551
Mean	46.387	6.733	2.691

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each binary outcome is rescaled by multiplying by 100. All regressions control for mother's race/ethnicity×birth county×birth month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.7: Effects of Exposure to Above-3-SD Heat on the Timing of Infant Hospital Readmission

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Timing of Readmission						
	Birth-7 days	7-28 days	28-100 days	100 days-1 year	1-2 years	2-5 years	After 5 years
# Days above-3-SD heat in trimester 1	0.050*	-0.003	0.081*	0.021	-0.019	0.034	-0.047
	(0.026)	(0.027)	(0.042)	(0.028)	(0.033)	(0.040)	(0.046)
# Days above-3-SD heat in trimester 2	0.001	0.045	0.019	0.096*	0.021	0.070*	0.083
	(0.028)	(0.030)	(0.044)	(0.050)	(0.032)	(0.037)	(0.073)
# Days above-3-SD heat in trimester 3	-0.043	-0.013	0.028	0.007	0.023	0.025	0.093
	(0.038)	(0.028)	(0.044)	(0.076)	(0.036)	(0.049)	(0.091)
Observations	75328	75328	75328	75328	75328	75328	75328
Adjusted R^2	0.320	0.274	0.287	0.244	0.176	0.335	0.815
Mean	1.895	1.277	1.991	1.946	1.231	1.327	1.093

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for infant's race×infant's sex×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.8: Robustness to Including Two-Year Leads in Temperature Exposure

	(1) Prenatal hospitalization	(2) Dehydration at birth	(3) Readmission
# Days above-3-SD heat in trimester 1	-0.042	-0.002	0.125
	(0.047)	(0.005)	(0.110)
# Days above-3-SD heat in trimester 2	0.160**	0.009*	0.252**
	(0.068)	(0.005)	(0.123)
# Days above-3-SD heat in trimester 3	0.139**	0.005	0.084
	(0.065)	(0.004)	(0.152)
# Days above-3-SD heat in trimester 1 (placebo)	-0.024	0.003	-0.158
	(0.052)	(0.005)	(0.124)
# Days above-3-SD heat in trimester 2 (placebo)	0.037	-0.003	-0.074
	(0.053)	(0.005)	(0.084)
# Days above-3-SD heat in trimester 3 (placebo)	0.107	0.021***	0.027
	(0.098)	(0.006)	(0.147)
Observations	35736	60559	60559
Adjusted R^2	0.445	0.006	0.601
Mean	3.995	0.026	8.686

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. Column (1) controls for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. For maternal outcome, we use the data collapsed at the race×birth-county×birth-year-month level. Columns (2) and (3) control for infant's race×infant's sex×birth-county×birth-month fixed effects, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level for infant outcomes. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.9: Effects of Exposure to Above-3-SD Heat on Infant Health, Controlling for Contemporaneous Temperature

	(1) Dehydration at birth	(2) Readmission	(3) Dehydration at birth	(4) Readmission
# Days above-3-SD heat in trimester 1	-0.001	0.110	-0.001	0.142
	(0.005)	(0.152)	(0.005)	(0.117)
# Days above-3-SD heat in trimester 2	0.007*	0.394*	0.006	0.387**
	(0.004)	(0.216)	(0.004)	(0.185)
# Days above-3-SD heat in trimester 3	0.004	0.131	0.005	0.135
	(0.004)	(0.225)	(0.004)	(0.221)
# Days above-3-SD heat in the first year	0.001	0.159		
	(0.003)	(0.137)		
# Days above-3-SD heat, averaged across all observable years			0.000	0.508
			(0.011)	(0.354)
Observations	66948	66948	66948	66948
Adjusted R^2	0.020	0.663	0.020	0.663
Mean	0.026	8.686	0.026	8.686

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for infant's race ×infant's sex×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×female×birth-county×birth-year-month level. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.10: Effects of Exposure to Above-3-SD Heat on Maternal and Infant Health in New York

	(1) Prenatal hospitalization	(2) Dehydration at birth	(3) Readmission
# Days above-3-SD heat in trimester 1	-0.025	-0.003	0.134
	(0.048)	(0.005)	(0.097)
# Days above-3-SD heat in trimester 2	0.201**	0.010*	0.224
	(0.084)	(0.006)	(0.146)
# Days above-3-SD heat in trimester 3	0.171***	-0.002	-0.001
	(0.048)	(0.003)	(0.174)
Observations	30341	53002	53002
Adjusted R^2	0.509	0.005	0.328
Mean	4.032	0.030	7.274

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, $\beta_{t,8}$, from equation (1). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. Column (1) controls for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. For maternal outcome, we use the data collapsed at the race×birth-county×birth-year-month level. Columns (2) and (3) control for infant's race×infant's sex×birth-county×birth-month fixed effects, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level for infant outcomes. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table B.11: Effects of Exposure to Above-90-Degree Heat on Maternal and Infant Health in New York

	(1) Prenatal hospitalization	(2) Dehydration at birth	(3) Readmission
# Days above-90-degree heat in trimester 1	0.060	0.002	-0.005
	(0.041)	(0.004)	(0.086)
# Days above-90-degree heat in trimester 2	0.076*	0.008**	0.177**
	(0.043)	(0.003)	(0.082)
# Days above-90-degree heat in trimester 3	0.191**	-0.004	-0.018
	(0.090)	(0.004)	(0.150)
Observations	30341	53002	53002
Adjusted R^2	0.508	0.005	0.328
Mean	4.032	0.030	7.274

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients on the number of days above-90-degree heat in each trimester. Each regression is analogous to equation (1) except that it controls for the number of days in each temperature bin from Appendix Figure A.1 (a) instead of the number of days in each SD bin from Appendix Figure A.1 (b). Robust standard errors, clustered by birth county, are in parentheses. Each outcome is rescaled by multiplying by 100. Column (1) controls for mother's race/ethnicity×birth-county×birth-month fixed effects, zip code level income quartiles, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. For maternal outcome, we use the data collapsed at the race×birth-county×birth-year-month level. Columns (2) and (3) control for infant's race×infant's sex×birth-county×birth-month fixed effects, birth-state×birth-year fixed effect, a quadratic time at the county×calendar month level, and a cubic polynomial in precipitation. We use the data collapsed at the race×sex×birth-county×birth-year-month level for infant outcomes. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Appendix C. Biological Mechanisms Linking Prenatal Temperature Exposure with Maternal and Infant Health

A growing medical literature discusses the biological mechanisms through which extreme heat could be damaging to human health. Exposure to extreme temperature can be particularly risky for pregnant women. The underlying issue is that pregnant women are not able to regulate temperature as efficiently as non-pregnant individuals due to the physiologic changes they undergo during gestation (Schifano et al., 2016), which means that elevated body temperature during pregnancy can lead to various complications. Heat exposure can alter placental blood flow patterns, which can reduce the integrity of the placenta and increase the chance of abruption (He et al., 2018). Heat could further raise the likelihood of other serious pregnancy complications, including hypertension, preeclampsia, and prolonged premature rupture of membranes (Beltran et al., 2014, Yackerson et al., 2007). In addition, elevated temperature can increase the fetal heart rate and lead to uterine contractions (Vaha-Eskeli and Erkkola, 1991). All of these issues can translate into women needing to be hospitalized during pregnancy and experiencing complications at childbirth.

Hot temperatures may be particularly damaging for infants, too. When body temperature increases, blood flow shifts from the vital organs to underneath the skin's surface to facilitate cooling (Astrand et al., 2003). When too much blood is diverted, the body's capacity to regulate its temperature may be hindered, which puts increased stress on critical organs, including the heart and lungs (King, 2004). These issues can cause newborns, whose organs are still developing and who have a higher heart rate than adults, to exhibit adverse outcomes at birth and beyond.

In sum, there are clear biological reasons to support the idea that exposure to extreme heat during pregnancy could be damaging for both mothers and their children. The goal of this paper is to use large-scale administrative data with a quasi-experimental research design to quantify these impacts, thereby shedding light on the environmental determinants of maternal and infant health complications and the possible mechanisms underlying previously documented long-term effects of prenatal exposure to heat on outcomes in adulthood.