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

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Abstract

We use temperature variation within narrowly-defined geographic and demographic cells to show that exposure to extreme temperature increases the risk of maternal hospitalization during pregnancy. This effect is driven by emergency hospitalizations for various pregnancy complications, suggesting that it represents a deterioration in underlying maternal health rather than a change in women's ability to access health care. The effect is larger for Black women than women of other races, suggesting that, without significant adaptation, projected increases in extreme temperatures over the next century may further exacerbate racial disparities in maternal 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 discussions about maternal health have focused on the role of the health care system, but we know much less about other—*environmental*—determinants of maternal health or the disparities within it.[1] This paper studies the impact of an environmental factor that is becoming increasingly relevant due to the growing scientific consensus that climate change is contributing to an increase in extreme weather events, especially those linked to heat.[2]

Specifically, we estimate the causal effect of exposure to extreme temperature during pregnancy on maternal hospitalizations, using the universe of administrative inpatient discharge records from three U.S. states: Arizona, New York, and Washington. We leverage variation in temperature within narrowly-defined geographic and demographic cells, and control for birth-county×birth-month×race fixed effects, birth-state×birth-year fixed effects, and a quadratic time trend interacted with birth-county×birth-month indicators.

A growing literature demonstrates that accounting for adaptation is important for measuring the effects of temperature and climate change more broadly (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Barreca et al., 2015; 2016; Carleton et al., 2018). 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. As such, temperature *deviations* from the local area norm may be particularly important, and we model exposure to extreme temperature in terms of standard deviations relative to each county's temperature mean in every month. In addition, as an alternative way of capturing the role of

[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] For one resource summarizing the scientific literature surrounding climate change, see: `https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world`.

adaptation, we present estimates from models that include different bins of absolute temperature levels, separately for historically cooler and hotter counties.

We find that exposure to extreme temperature has adverse impacts on women's pregnancy health. We estimate that an additional day during pregnancy with an average temperature that is at least three standard deviations above the county's monthly mean (hereafter referred to as "above-3-SD" temperature) increases the likelihood that a woman is hospitalized during pregnancy by 0.1 percentage points, which is a 2.2 percent effect at the sample mean. This effect is driven by hospitalizations for emergency and urgent reasons, suggesting that it represents a deterioration in underlying maternal health rather than a change in women's ability to access health care. Analysis of primary diagnosis codes further indicates that this effect is driven by hospitalizations for various pregnancy complications, such as hypertension, which can be life-threatening.[3]

Interestingly, we find adverse impacts on maternal hospitalizations from exposure to unusually warm temperatures both in the summer and non-summer months. Thus, behavioral responses to temperature deviations from the norm—such as engaging in more outdoor physical activity on unusually warm winter days and risking fatigue and/or dehydration—may contribute to explaining the maternal health impacts. Analysis of secondary diagnosis codes in the inpatient data shows that above-3-SD temperatures increase hospitalizations with secondary diagnoses for diseases associated with the urinary and digestive systems (including kidney and urinary tract infections, and gallbladder and liver conditions), for which dehydration is a known risk factor.

Results from models with absolute temperature bins further indicate that accounting for adaptation is important. We split our sample into mothers residing in counties with above- and below-median average temperatures during the analysis period, and find that, in the historically cooler counties, an additional day during pregnancy with a mean temperature of at least 90°F increases the likelihood of an emergency or urgent maternal hospitalization by 0.1 percentage points (5.1 percent at the sub-sample mean). By contrast, the effect of such a hot day in the historically hotter counties is very small and statistically insignificant. This finding suggests that, because historically cooler places are likely less adapted to extreme heat than historically hotter areas, mothers residing in cooler places bear a disproportionate cost to their pregnancy health. These findings, together

[3] Hypertensive disorders represent the fifth leading cause of maternal pregnancy-related death (Kuriya et al., 2016).

with results on exposure to "above-3-SD" temperature, imply that extreme heat is detrimental to women's pregnancy-related health when it constitutes a deviation from the local area norm.

We also demonstrate that the health cost of extreme temperature is not distributed equally across racial groups. For non-Hispanic Black women, an additional day with above-3-SD temperature during pregnancy raises the likelihood of hospitalization by 0.4 percentage points, or 5 percent. For non-Hispanic white women, the corresponding magnitude is a 0.1 percentage point increase, or 2.4 percent. We find even smaller and statistically insignificant impacts of above-3-SD temperature for Hispanic women and women of other races. Moreover, we find that unusually cold days—those with an average temperature that is at least three standard deviations *below* the county's monthly mean—are also detrimental for Black women's pregnancy health. An additional day with below-3-SD temperature during pregnancy raises Black women's likelihood of hospitalization by 0.4 percentage points (5 percent).

Our study contributes to a burgeoning literature, which has identified adverse short-term impacts of extreme temperature on several outcomes, including elderly mortality (Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011), population-level 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). Multiple studies have further documented negative effects of *in utero* heat exposure on birth outcomes—including birth weight, gestation length, and the probability of stillbirth (e.g., Deschênes et al., 2009; Dadvand et al., 2011; Schifano et al., 2016; Auger et al., 2017; Ha et al., 2017a,b; Kuehn and McCormick, 2017; Barreca and Schaller, 2019; Bekkar et al., 2020)—highlighting the sensitivity of the prenatal period to extreme heat.[4] To the best of our knowledge, only one prior study has analyzed the relationship between prenatal temperature exposure and *maternal* health, using information on mothers' pregnancy risk factors and labor/delivery complications reported on birth certificates (Cil and Cameron, 2017). However, as multiple validation studies indicate that maternal pregnancy risk factors, obstetric procedures, and complications of labor and delivery are heavily under-reported on birth certificates (Parrish et al., 1993; Buescher et al., 1993; Piper et al, 1993; Dobie et al.,

[4]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). Two recent studies have also shown that early life heat exposure has lasting negative effects on long-term cognitive ability (Hu and Li, 2019) and adult earnings (Isen, Rossin-Slater, and Walker, 2017).

1998; Reichman and Hade, 2001; DiGiuseppe et al., 2002; Roohan et al., 2003; Lydon-Rochelle et al., 2005), and the degree of under-reporting varies with maternal demographic characteristics and birth outcomes (Reichman and Schwartz-Soicher, 2007), analyses of maternal health based on birth records data are likely subject to bias from non-random measurement error. We address this issue by instead using inpatient discharge records that provide more accurate information on maternal health based on diagnoses associated with each hospitalization. Further, our empirical strategy explores the role of adaptation, which we find to be important for understanding the effects of extreme temperature on women's pregnancy health.

Our findings suggest that the projected increase in extreme weather over the next century may contribute to further worsening of maternal health. At the same time, adaptation can play an important role in mitigating these impacts—in our analysis, hot temperatures appear to only be damaging to maternal health if they are unusual. Moreover, since Black women are both more likely to experience extreme temperature during pregnancy (due to historical differences in housing policies and residence locations, see Hoffman et al., 2020) and have less access to adaptive technologies such as air conditioning (O'Neill et al., 2005; Gronlund, 2014), our estimates imply that climate change could further exacerbate racial inequities in maternal health.

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 2.72 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 childbirth.[5] Since less than two percent of all births occur outside of hospitals during our analysis time period, we observe the

[5]We use DRG 370-375 or 765-768 & 774-775, depending on the version of DRG.

near-universe of all mothers giving birth in our analysis states.[6] We identify maternal hospitalizations during pregnancy by tracking women's inpatient visit records that occurred in the 9 months before delivery. The primary and secondary diagnosis codes associated with each visit allow us to investigate the causes for hospitalization.

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.[7] We then merge these data to the maternal inpatient records, using information on the mother's county of residence at the time of delivery. We use the mother's year and month of delivery to assign exposure to temperature during pregnancy by assuming a 40-week pregnancy duration for all observations.[8]

To account for the large amount of variation in average temperatures across geographic areas that could generate differing adaptation responses, 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. This normalization enables us to identify extreme weather while accounting for long-term adaptation to historical temperature trends.

In addition, we measure exposure based on the number of days during pregnancy that fall into each of ten absolute temperature bins, ranging from less than 10°F to 90°F or more. To examine the role of adaptation in these models, we study differences between mothers residing in counties with below- and above-median daily mean temperatures averaged over the whole data period.

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

[7] We aggregate weather station-level data to the county level by taking an average of all weather stations with non-missing data in a given county.

[8] Information on gestational age is only available via diagnosis codes in a small share of children's hospitalization records; this information is not available in the maternal inpatient records (and we cannot link mothers to their children in our data). 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).

Distribution of Temperature Exposure and Sample Means. Figure 1 shows the distribution of daily average temperature in Arizona, New York, and Washington during our sample period. We compute the average number of days during pregnancy falling into each of the temperature bins expressed using (a) standard deviations, and (b) absolute temperature thresholds. As reported in Panel A of Table 1, the average pregnant woman experiences 5.6 days with mean temperature between two and three standard deviations above the county-month mean, and 0.2 days with mean temperature of at least three standard deviations above the county-month mean. Using absolute temperatures, the average pregnant woman experiences 3.9 days with mean temperature falling between 80 and 90 degrees, and 0.8 days with mean temperature above 90 degrees.

Panel B of Table 1 provides means of maternal health outcomes that we analyze (expressed as rates per 100 mothers). Approximately 4.5 percent of women are hospitalized during pregnancy, with the most common primary diagnosis being a pregnancy-related complication (ICD-9 codes 640-649). Approximately 3.1 percent of women are hospitalized for emergency or urgent reasons. In Panel C of Table 1, we report the race/ethnicity distribution of our sample—the mothers in our data are 52.0 percent non-Hispanic white, 12.5 percent non-Hispanic Black, 20.1 percent Hispanic, and 15.4 percent in other racial/ethnic groups.

3 Empirical Strategy

A robust medical literature discusses the biological mechanisms through which extreme temperature could be damaging to human health, and highlights that it 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 both elevated and lowered 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). Both extreme heat and extreme cold can 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.

The goal of this paper is to quantify the causal relationship between extreme temperature and maternal health. A central challenge is that exposure to extreme weather 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 mothers 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. We first 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 (non-Hispanic White, non-Hispanic Black, Hispanic, Asian American, Native American, and other). We then use the following regression model to estimate the effects of exposure to extreme temperature during pregnancy:

$$Y_{c,y,m,r} = \alpha + \sum_{j=1, j\neq 5 or 7}^{8 or 10} \beta_j Temp^j_{c,y,m} + \gamma f(Precip_{c,y,m}) + \theta_{c,m,r} + \eta_{y,s(c)} + \delta_{c,m} \times f(y) + \epsilon_{c,y,m,r} \quad (1)$$

where $Y_{c,y,m,r}$ is an outcome for a mother residing in county c, giving birth in year y and month m, in race/ethnicity group r. We rescale the outcomes by multiplying by 100 (e.g., the number of mothers admitted to the hospital during pregnancy per 100 mothers). The variables $Temp^j_{c,y,m}$ represent the number of days during pregnancy 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 3 SDs or more, as illustrated in Figure 1(a). In alternative specifications, we instead use the number of days during pregnancy falling into each of the ten bins of absolute temperature ranges, from less than 10°F to 90°F or higher, as shown in Figure 1(b).

In the relative temperature exposure models, we omit the [0,1) SD bin as the reference group, while in the absolute temperature exposure models, we omit the [60, 70)°F bin. Thus, the β_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 either the [0,1) SD range or the [60, 70)°F range. We are particularly interested in coefficients on the effects of an additional above-3-SD day during pregnancy (β_8 in the relative exposure model) and an additional above-90-degree day during pregnancy (β_{10} in the absolute exposure model).

We control for indicators for the bottom and the top terciles of mean precipitation during pregnancy, $f(Precip_{c,y,m})$. $\theta_{c,m,r}$ are fixed effects for every birth-county×birth-month×race 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-July-specific trends), which we model with a quadratic polynomial. To further account for potential sorting based on temperature, we control for the share of mothers in each cell whose ZIP codes of residence fall into different quartiles of the state's median income distribution.[9] We weight all regressions by cell size.[10] Because weather is highly spatially correlated, we cluster our standard errors on the commuting zone level.[11]

Our model identifies the effects of extreme temperature 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 July 2010 and a Black woman giving birth in the same county in July 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 July births, while controlling for the average difference in temperature

[9]The HCUP data includes information on the patient's ZIP code of residence along with a categorical variable (*MEDINCSTQ*) that provides the quartile classification of the estimated median household income for the state. According to HCUP: "The cut-offs for the quartile designation for each state is determined using ZIP Code-demographic data obtained from Claritas. The assignment of MEDINCSTQ for a particular discharge is based on the median income of the patient's ZIP Code. The quartiles are identified by values of 1 to 4, indicating the poorest to wealthiest populations, respectively. Because these estimates are updated annually, the value ranges for the MEDINCSTQ categories vary by year and state." Source: `https://www.hcup-us.ahrq.gov/db/vars/sasddistnote.jsp?var=medincstq`.

[10]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.

[11]Our results are also robust to using an alternative adjustment of standard errors to reflect spatial dependence, as modeled by Conley (1999) and implemented by Hsiang (2010). Results available upon request.

exposure between all New York state births in 2010 and 2011.

A potential concern for our empirical design is that there remains insufficient variation in temperature exposure after we condition on all of the fixed effects and trends just described. In Appendix Figures A.1(a) and (c), we plot histograms of the residuals from a regression of the number of days of pregnancy exposure to above-3-SD temperature and above-90-degree temperature, respectively, on the birth-county×birth-month×race fixed effects, birth-state×birth-year fixed effects, and county×calendar-month-specific quadratic trends. The graphs show that there is more residual variation in the top relative temperature bin than in the top absolute temperature bin. In addition, as expected, there is more residual variation in extreme temperatures than in more typical temperatures (Appendix Figures A.1(b) and (d)). That said, we present estimates from both the relative and absolute exposure models, and we show that our results are not sensitive to excluding different fixed effects and trends.

Identifying Assumption. Our estimates of β_j represent causal effects of pregnancy 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 health. While this assumption is inherently untestable, we present some indirect tests to assess its plausibility.

First, we check whether there is any systematic relationship between the 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 maternal ZIP code income quartiles. Panel A of Appendix Table B.1 shows that temperature exposure is not correlated with the racial/ethnic composition of mothers in our data. In panel B of Appendix Table B.1, we do not observe any significant relationship between exposure to different temperature bins during pregnancy and the share of mothers residing in ZIP codes in each quartile of the median income distribution.[12]

Second, to address the possibility that extreme temperature could influence fertility rates and

[12] In supplementary analyses, we have also examined the relationship between temperature and the sex ratio at birth, finding no significant effects (results available upon request). The lack of relationship between temperature exposure and infant sex suggests that there is no detectable 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).

thus affect selection into our sample of analysis, we estimate models that use the number of births in each county-month cell as the outcome.[13] Appendix Table B.2 shows that none of the temperature bins is correlated with the number of births in our analysis.

Third, we test the robustness of our results to including hypothetical exposure to temperature assuming a mother gave birth either one or two years before her actual delivery year-month, or one year after her actual delivery year-month. As we show below, the main effects of exposure during pregnancy remain strong and significant even when we add lags and leads of temperature exposure.

4 Results

Results from models with relative temperature bins. Table 2 and Figure 2 show that exposure to extreme temperature raises the likelihood that a mother is hospitalized during pregnancy. Specifically, we find that an additional day with above-3-SD temperature during pregnancy raises the likelihood that a mother is hospitalized by 0.1 percentage points, which translates into a 2.2 percent effect size when evaluated at the sample mean. In column (2) of Table 2, we show that the increase in prenatal hospitalizations is driven by visits for emergency and urgent reasons rather than scheduled admissions, which suggests that the effect represents a deterioration in underlying maternal health as opposed to an improvement in health care access or utilization. Moreover, while the effect of exposure to above-3-SD temperature is particularly strong, we also find some evidence that exposure to days with temperature between 2 and 3 SDs above the county-month mean increases maternal hospitalizations during pregnancy (by 0.01 percentage points, or 0.3 percent). When we explore the effects of trimester-specific exposure in Appendix Figure A.2, we find that above-3-SD temperature during the second and third trimesters raises the likelihood of hospitalization by 0.22 and 0.12 percentage points, respectively.[14]

Next, we examine the primary causes for maternal hospitalizations. In Figure 3, we present coefficient estimates and 95% confidence intervals on exposure to above-3-SD temperature from models that use indicators for various primary diagnoses codes associated with the pregnancy hospitalization as outcomes. We find that the increase in maternal hospitalizations in response to

[13] We have used national vital statistics data to compare to the number of births in our data, confirming that our data closely tracks the universe of births.

[14] Since we assume a 40-week pregnancy length for all mothers in the analysis, it is worth noting that trimester-specific estimates are subject to measurement error.

extreme temperature is driven by a range of pregnancy complications, including hypertension (ICD 642) and excessive vomiting (ICD 643), as well as a range of other (less common) complications and conditions (ICD 646, 648, 649). Appendix Table B.3 shows the full set of coefficients corresponding to each SD bin in our regression model.

We also explore the impacts of season-specific temperature deviations by estimating regression models that include season-specific relative temperature exposure bins. Specifically, we include bins for summer months (May-September), bins for spring and fall months (March-April and October-November), and bins for winter months (December-February). Appendix Figure A.3 presents the results. The confidence intervals for the estimates on the effects of exposure to above-3-SD temperatures in the three seasonal categories overlap, so we cannot attribute our impacts to being driven by any one season. That said, it does appear that abnormally warm temperatures in non-summer months increase the likelihood of maternal hospitalization during pregnancy. This suggests that behavioral mechanisms may contribute to explaining our maternal health impacts. For instance, pregnant women may spend more time outdoors in response to unusually warm temperatures in non-summer months, potentially increasing their risk of contracting an infection due to exposure to more people than they would have otherwise encountered. Alternatively, pregnant women may engage in more outdoor physical activity in warmer weather during non-summer months, leading to a greater risk of fatigue and/or dehydration.

While we do not have any data to precisely explore these behavioral channels, we can analyze secondary diagnosis codes in the hospitalizations data that are reported alongside the primary codes shown in Figure 3. For this analysis, we focus on the most common secondary diagnoses other than pregnancy complications. Appendix Table B.4 presents results from regression models that use as outcomes indicators for prenatal hospitalizations associated with various categories of secondary diagnoses. We find that exposure to above-3-SD temperatures significantly increases the likelihood of hospitalizations for diseases associated with the urinary system (including kidney and urinary tract infections) and diseases of the digestive system (including gallbladder and liver conditions). Dehydration is a known risk factor for many of these conditions, making it a plausible mechanism for explaining the link between temperature and these hospitalizations.

Differences by maternal race and ethnicity. We find that the effects of extreme temperature on prenatal hospitalization are different across mothers from different racial/ethnic groups.[15] Table 3 shows that the estimated adverse effect of extreme temperature is particularly large for non-Hispanic Black mothers—we observe that an additional day with either above-3-SD or below-3-SD temperature during pregnancy increases the likelihood of hospitalization by 0.4 percentage points, or 5 percent at the subsample mean. By contrast, for non-Hispanic white mothers, we only find a 0.1 percentage point (2.4 percent) increase in the likelihood of prenatal hospitalization associated with exposure to above-3-SD temperature. The p-values from tests of the difference in coefficients on exposure to above-3-SD and below-3-SD temperature between white and Black mothers are 0.018 and <0.001, respectively.

Results from models with absolute temperature bins. While we use relative temperature exposure based on standard deviations relative to each county's mean to account for adaptation, we also present estimates from more standard models that include absolute temperature bins. Here, we account for differences in local area adaptation by splitting the sample into counties with below- and above-median daily mean temperatures averaged over the whole data period.

Table 4 shows that exposure to temperature 90 degrees or more is associated with an increase in the likelihood of maternal hospitalization during pregnancy in the historically cooler counties. Specifically, an additional day with above-90-degree temperature increases the likelihood of an emergency or urgent hospitalization during pregnancy by 0.1 percentage points (or 5.1 percent) for mothers in below-median counties. For mothers in the above-median counties, the corresponding coefficient is much smaller and statistically insignificant.[16] The difference in the effects on emergency/urgent hospitalizations between mothers in below-median and above-median counties is statistically significant (p-value: 0.042).[17]

[15] When we estimate our models separately by race/ethnicity categories, we drop counties that have fewer than 50 mothers in the group under analysis. 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.

[16] Thus, when we pool all of the mothers in our data and estimate models using exposure to absolute temperature bins, we find a positive but statistically insignificant average effect on maternal hospitalizations (Appendix Table B.5).

[17] Table 4 also shows that, in the historically hotter counties, exposure to days in the 70-80 and 80-90 degree ranges slightly reduces the likelihood of maternal hospitalization during pregnancy. We interpret this as evidence that temperature in "normal" ranges may be advantageous for maternal health, possibly due to adaptation behavior (i.e., these are temperature ranges in which mothers feel most comfortable).

5 Additional Results

Results by state. In Appendix Tables B.6 and B.7, we analyze the effects of relative and absolute temperature exposure separately by state. We find significant effects of both unusually cold and unusually hot days in New York. Our sample size in New York is substantially larger than in Washington or Arizona, providing us with more power to identify statistically significant effects there. Moreover, we note that mothers in Arizona did not experience any above-3-SD days during our analysis period.

When we examine models that include absolute temperature bins separately by state (Appendix Table B.7), we find that the adverse effects of above-90-degree heat are present in both Washington and New York (with a much larger magnitude in Washington than in New York). Very hot days are much more rare in Washington and New York than they are in Arizona, and we find that the impacts on maternal hospitalizations are concentrated in the former states. Taken together, the state-specific results again highlight the importance of adaptation in understanding the effects of extreme temperature.

Sensitivity of estimates to including different controls. Appendix Table B.8 evaluates how the coefficient estimates change as we include different combinations of the ZIP code income controls, fixed effects, and trends. The results in column (6) come from our baseline model. The estimated coefficients on exposure to above-3-SD temperature are very similar across all of these different specifications, suggesting that the results in our preferred specification are not driven by a particular choice of fixed effects and trends. Rather, the inclusion of these controls allows us to deliver a conservative but precise estimate of the effect of extreme temperature on maternal health.

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 different leads and lags of temperature exposure. We define "lags" as temperature exposure *before* pregnancy, and "leads" as temperature exposure *after* pregnancy.

First, we consider two-year lags. That is, for every birth-county×birth-year-month, we calculate the hypothetical exposure to temperature assuming that the child had been born two years prior to his/her actual month of birth. We use a two-year (instead of a one-year) lag 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). Table 5 shows that our main results are robust to the inclusion of this placebo control. The point estimate for the effect of actual exposure to extreme temperature does not change when we control for placebo exposure, and the placebo coefficient stays insignificant.

We also consider one-year lags of temperature exposure to directly test whether fertility effects might be confounding our results. Columns (1) and (2) of Appendix Table B.9 show that our results are robust to including one-year lags, and the coefficients on one-year lags are small and insignificant. In addition, columns (3) and (4) of Appendix Table B.9 present results from models that include one-year leads of temperature exposure (i.e., hypothetical exposure assuming a child is born one year *after* his/her actual month of birth). We continue to find statistically significant effects of extreme temperature exposure on maternal hospitalizations even after controlling for temperature leads.

Controlling for air pollution. Prior research shows that pollution is highly correlated with weather and affects population health (e.g., Ye et al., 2012). To account for possible confounding by air pollution, we estimate our main models with additional controls for air quality index (AQI) categories as measured by the Environmental Protection Agency. Since AQI is not available for all counties and year-months in our analysis sample, we also re-estimate our main specifications using a sub-sample of the data with non-missing AQI measures. We find that our estimates are robust to including pollution controls (see Appendix Table B.10).

6 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 90°F in the average American county is forecasted to increase from about one to approximately 43 per year by 2070-2099 (Intergovernmental Panel on Climate Change, 2014). Understanding the health consequences of this increase in extreme temperature is critical for informing discussions about the costs of climate change and the possible benefits of mitigating policies. Moreover, the growing literature on the importance of adaptation suggests 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 temperature by documenting maternal health impacts. We use the universe of inpatient discharge records from three states and find that exposure to extreme temperature during pregnancy leads to an increase in women's emergency and urgent hospitalizations for pregnancy-related complications. The fact that the increase in hospitalizations during pregnancy is larger for Black mothers than for mothers in other racial groups suggests that climate change may exacerbate the already large racial gap in maternal health.

What do our estimates imply about the economic cost of extreme temperature? We conduct a back-of-the-envelope calculation by scaling our estimate of the impact of an additional day of exposure to above-3-SD temperature by the average number of such days experienced by pregnant women in our sample and by the total number of births in each year in the United States (based on the most recent available vital statistics data from 2018). This calculation suggests that there are approximately 910 additional maternal hospitalizations in the U.S. resulting from above-3-SD temperatures in every year.[18] HCUP data on hospital charges suggests that these excess hospitalizations cost approximately $10,050,040 (in $2018).[19] Similarly, we estimate that an additional day of exposure to temperature between 2 and 3 SDs relative to the county-month mean results in approximately 2,112 excess hospitalizations, costing around $23,324,747.[20] Of course, this calculation does not incorporate other costs associated with the deterioration in women's pregnancy health (including non-health costs such as foregone wages due to missed time at work) and does not capture the impacts of extreme temperature on other outcomes measured in the existing literature.

An important limitation of our study is that we are not able to measure maternal health

[18] This calculation is conducted as follows. We find that each day of exposure to above-3-SD temperature increases maternal hospitalizations by 0.1 percentage points (Table 2, col. 1). The average woman in our analysis sample experiences 0.24 such days (Table 1). And according to vital statistics data from 2018, there are 3,791,712 births per year (see: `https://www.cdc.gov/nchs/fastats/births.htm`). Thus, $0.001 \times 0.24 \times 3,791,712 = 910$.

[19] According to HCUP, the average charge associated with a hospitalization during pregnancy is $11,044 in 2018 dollars.

[20] This calculation is conducted as follows. We find that each day of exposure to the 2-3 SD temperature bin increases maternal hospitalizations by 0.01 percentage points (Table 2, col. 1). The average woman in our analysis sample experiences 5.57 such days (Table 1). Thus, $0.0001 \times 5.57 \times 3,791,712 = 2,112$. Multiplying by $11,044, the average charge, yields $23,324,747.

impacts not captured by the hospitalizations data. Just like measures of maternal health in birth records may miss 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

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

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. Shapiro (2015). Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 1900–2004. *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. and J. Schaller (2019). The Impact of High Ambient Temperatures on Delivery Timing and Gestational Lengths. *Nature Climate Change*, 1–6

Bekkar, B., S. Pacheco, R. Basu, and N. DeNicola (2020. Association of air pollution and heat exposure with preterm birth, low birth weight, and stillbirth in the US: a systematic review. *JAMA Network Open* 3(6): e208243-e208243.

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

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

Buescher, P. A., Taylor, K. P., Davis, M. H., and J. M. Bowling. (1993). The Quality of the New Birth Certificate Data: a Validation Study in North Carolina. *American Journal of Public Health* 83(8), 1163–1165

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

Cil, G. and T. A. Cameron. (2017). Potential Climate Change Health Risks from Increases in Heat Waves: Abnormal Birth Outcomes and Adverse Maternal Health Conditions. *Risk Analysis* 37(11), 2066–2079

Conley, T.G. (1999). GMM Estimation with Cross Sectional Dependence. *Journal of Econometrics* 92(1), 1–45

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.

DiGiuseppe, D.L., D. C. Aron, L. Ranbom, D. L. Harper and G. E. Rosenthal (2002). Reliability of Birth Certificate Data: a Multi-Hospital Comparison to Medical Records Information. *Maternal and Child Health Journal* 6(3), 169–179

Dobie, S.A., L. M. Baldwin, R. A. Rosenblatt, M. A. Fordyce, C. H. A. Andrilla and L. G. Hart (1998). How Well Do Birth Certificates Describe the Pregnancies They Report? The Washington State Experience with Low-risk Pregnancies. *Maternal and Child Health Journal* 2(3), 145–154

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

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

Graff Zivin, J., 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

Hoffman, J. S., V. Shandas, and N. Pendleton (2020). The effects of historical housing policies on resident exposure to intra-urban heat: A study of 108 US urban areas. *Climate* 8(1): 12.

Hostetter, M., and S. Klein (2018). In Focus: Reducing Racial Disparities in Health Care by Confronting Racism. *The Commonwealth Fund*, available at: `https://www.commonwealthfund.org/publications/newsletter-article/2018/sep/focus-reducing-racial-disparities-health-care-confronting`.

Hsiang, S.M (2010). Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences* 107(35), 15367–15372

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), 1775–1812.

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.

Kuriya, A., Piedimonte, S., Spence, A. R., Czuzoj-Shulman, N., Kezouh, A., and Abenhaim, H. A. (2016). Incidence and Causes of Maternal Mortality in the USA. *Journal of Obstetrics and Gynaecology Research*, 42(6), 661–668.

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

Lydon–Rochelle, M.T., V. L. Holt, J. C. Nelson, V. Cárdenas, C. Gardella, T. R. Easterling and W. M. Callaghan (2005). Accuracy of Reporting Maternal In-hospital Diagnoses and Intrapartum Procedures in Washington State Linked Birth Records. *Paediatric and Perinatal Epidemiology* 19(6), 460–471

Nelson, A. (2002). Unequal Treatment: Confronting Racial and Ethnic Disparities in Health Care. *Journal of the National Medical Association* 94(8): 666.

O'Neill, M. S., A. Zanobetti and J. Schwartz (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

Parrish, K.M., V. L. Holt, F. A. Connell, B. Williams and J. P. LoGerfo (1993). Variations in the Accuracy of Obstetric Procedures and Diagnoses on Birth Records in Washington State, 1989. *American Journal of Epidemiology* 138(2), 119–127

Petersen, E. E., N. L. Davis, D. Goodman, S. Cox, N. Mayes, E. Johnston, C. Syverson, K. Seed,

C. K. Shapiro-Mendoza, W. M. Callaghan and W. Barfield (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

Piper, J.M., E. F. Mitchel Jr, M. Snowden, C. Hall, M. Adams and P. Taylor (1993). Validation of 1989 Tennessee Birth Certificates Using Maternal and Newborn Hospital Records. *American Journal of Epidemiology* 137(7), 758–768

Reichman, N.E. and E. M. Hade (2001). Validation of Birth Certificate Data: a Study of Women in New Jersey's HealthStart Program. *Annals of epidemiology* 11(3), 186–193

Reichman, N. E. and O. Schwartz-Soicher (2007). Accuracy of birth certificate data by risk factors and outcomes: analysis of data from New Jersey. *American Journal of Obstetrics and Gynecology*, 197(1): 32-e1.

Roohan, P.J., R. E. Josberger, J. Acar, P. Dabir, H. M. Feder, and P. J. Gagliano (2003). Validation of Birth Certificate Data in New York State. *Journal of Community Health* 28(5), 335–346

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

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

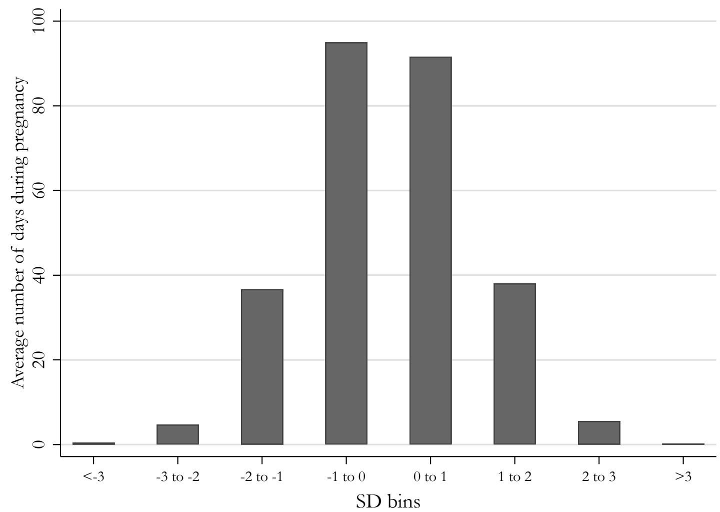
Xu, Z., R. A. Etzel, H. Su, C. Huang, Y. Guo, and S. Tong (2012). Impact of Ambient Temperature on Children's Health: A Systematic Review. *Environmental Research* 117, 120–131

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

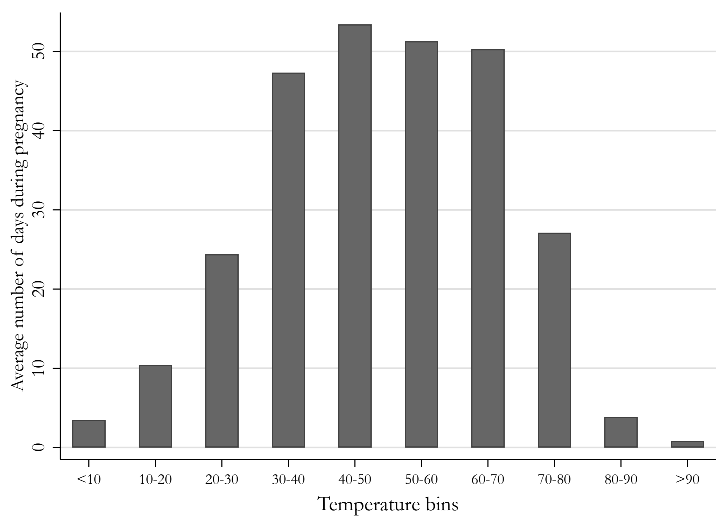
Ye, X., R. Wolff, W. Yu, P. Vaneckova, X. Pan, and S. Tong (2012). Ambient Temperature and Morbidity: A Review of Epidemiological Evidence. Environmental Health Perspectives 120 (1), p. 19.

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

7 Figures



(a) Using 8 SD bins



(b) Using 10 temperature bins

Figure 1: Distribution of Daily Average Temperature During Pregnancy

Sources: NOAA weather data.

Notes: This figure shows the overall average number of days during pregnancy falling into each of the SD and absolute temperature bins denoted on the $x-$axis. We compute daily average temperature by taking the 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. To create SD bins, we normalize the daily average temperature by subtracting the monthly mean and dividing it by standard deviation.

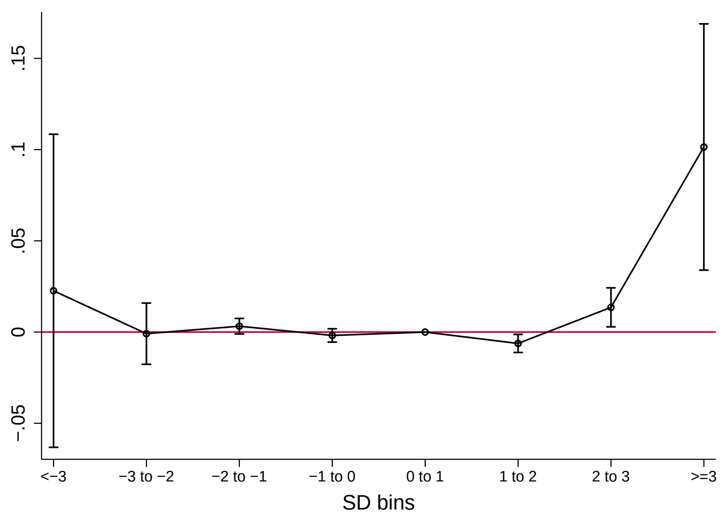


Figure 2: Effect of Temperature Deviations During Pregnancy on Maternal Hospitalization

Notes: The figure plots regression coefficients (β_j) from equation (1) for each SD bin (j) with 95% confidence intervals. The outcome is rescaled by multiplying by 100. Standard errors are clustered by the commuting zone level. The estimation 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 series of indicators for terciles of precipitation in each trimester. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

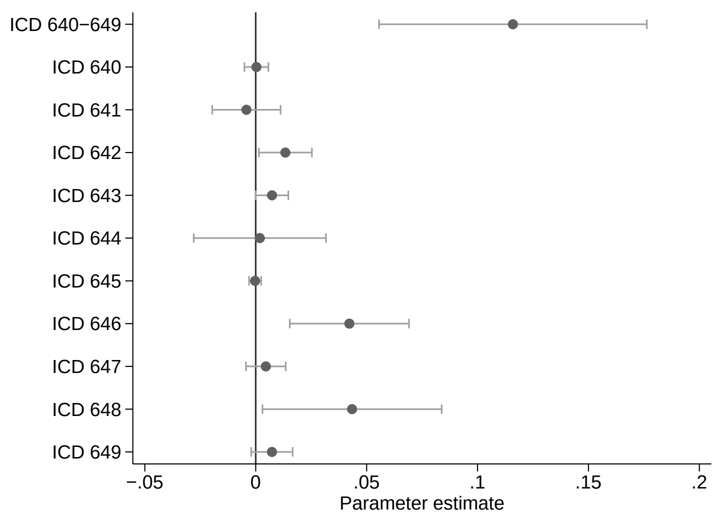


Figure 3: Effects of Above-3-SD Temperature During Pregnancy on Maternal Hospitalization, by Primary Diagnosis Categories

Notes: The figure plots separate regression coefficients (β_8) from equation (1) for temperature exposure above 3-SD-heat during pregnancy with 95% confidence intervals for each diagnosis category. Outcomes are rescaled by multiplying by 100. ICD codes 640-649 indicate "complications mainly related to pregnancy." The definition of each sub-category is as follows. ICD 640: Hemorrhage in early pregnancy; ICD 641: Antepartum hemorrhage abruptio placentae and placenta previa; ICD 642: Hypertension complicating pregnancy childbirth and the puerperium; ICD 643: Excessive vomiting in pregnancy; ICD 644: Early or threatened labor; ICD 645: Late pregnancy; ICD 646: Other complications of pregnancy not elsewhere classified; ICD 647: Infectious and parasitic conditions in the mother classifiable elsewhere but complicating pregnancy childbirth or the puerperium; ICD 648: Other current conditions in the mother classifiable elsewhere but complicating pregnancy childbirth or the puerperium; ICD 649: Other conditions or status of the mother complicating pregnancy, childbirth, or the puerperium. Standard errors are clustered by the commuting zone 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 series of indicators for terciles of precipitation in each trimester. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

8 Tables

Table 1: Summary Statistics

Panel A. Exposure to temperature extremes	
Average number of days during pregnancy with mean temperature	
Between 2 and 3 SDs	5.570
Above 3 SDs	0.240
Between 80 and 90^oF	3.874
Above 90^oF	0.830
Panel B. Maternal health outcomes (per 100 mothers)	
Any hospitalization during pregnancy	4.530
Emergency/urgent hospitalization during pregnancy	3.078
Primary Diagnoses at prenatal hospitalization	
Pregnancy-related complications (ICD 640-649)	4.086
Hemorrhage in early pregnancy (ICD 640)	0.043
Antepartum hemorrhage (ICD 641)	0.226
Hypertension complications (ICD 642)	0.231
Excessive vomiting in pregnancy (ICD 643)	0.243
Early or threatened labor (ICD 644)	1.203
Late pregnancy (ICD 645)	0.008
Other complications (ICD 646)	0.668
Infectious and parasitic conditions (ICD 647)	0.094
Other current conditions (ICD 648)	1.258
Other conditions (ICD 649)	0.111
Panel C. Maternal race (per 100 mothers)	
Non-Hispanic white	52.041
Non-Hispanic Black	12.469
Hispanic	20.131
Other	15.359
Observations	41715

Sources: NOAA weather data and HCUP databases.

Notes: We use daily level temperature data from NOAA to compute the average temperature exposure during pregnancy in panel A. For panels B and C, we use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

Table 2: Effects of Temperature Deviations During Pregnancy on Maternal Hospitalization

	(1)	(2)
	Prenatal hospitalization	
	Any	Emergency/urgent
# Days below -3 SD temp	0.023	0.023
	(0.042)	(0.027)
# Days between -3 to -2 SD temp	-0.001	-0.001
	(0.008)	(0.006)
# Days between -2 to -1 SD temp	0.003	-0.001
	(0.002)	(0.003)
# Days between -1 to 0 SD temp	-0.002	-0.004**
	(0.002)	(0.002)
# Days between 1 to 2 SD temp	-0.006**	-0.009***
	(0.002)	(0.002)
# Days between 2 to 3 SD temp	0.014**	0.011
	(0.005)	(0.007)
# Days above 3 SD temp	0.101***	0.071***
	(0.033)	(0.024)
Observations	41715	41715
Adjusted R^2	0.474	0.501
Mean	4.530	3.078

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. 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 3: Effects of Temperature Deviations During Pregnancy on Maternal Hospitalization, by Race/Ethnicity

	(1)	(2)	(3)	(4)
	Any prenatal hospitalization			
	White	Black	Hispanic	Other
# Days below -3 SD temp	-0.024	0.360***	0.189*	-0.045
	(0.073)	(0.101)	(0.106)	(0.101)
# Days below -3 to -2 SD temp	0.009	-0.034	-0.047***	0.005
	(0.009)	(0.030)	(0.013)	(0.018)
# Days below -2 to -1 SD temp	0.002	-0.001	0.012	-0.003
	(0.004)	(0.005)	(0.008)	(0.008)
# Days below -2 to -1 SD temp	-0.001	0.000	-0.006	-0.005
	(0.002)	(0.005)	(0.005)	(0.004)
# Days below 1 to 2 SD temp	-0.004	-0.007	-0.007	-0.019*
	(0.005)	(0.004)	(0.007)	(0.010)
# Days below 2 to 3 SD temp	0.019**	-0.012	0.022	0.027*
	(0.008)	(0.012)	(0.027)	(0.015)
# Days above 3 SD temp	0.092**	0.394***	0.036	0.012
	(0.033)	(0.136)	(0.058)	(0.106)
Observations	8539	4412	5022	12497
Adjusted R^2	0.448	0.458	0.458	0.246
Mean	3.866	7.885	5.696	3.889

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients, β_j from equation (1). Robust standard errors, clustered by commuting zone, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions control for 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 series of indicators for terciles of precipitation in each trimester. We use the data collapsed at the race×birth-county×birth-year-month level. We drop counties with fewer than 50 mothers in each race/ethnicity category. Cell size weights are used. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Effects of Absolute Temperatures During Pregnancy on Maternal Hospitalization, Historically Cooler vs. Historically Hotter Counties

	(1)	(2)
	Prenatal hospitalization	
	Any	Emergency/urgent
Panel A. Historically cooler counties (below-median average temperatures)		
# Days below 10 degrees	0.001	0.001
	(0.024)	(0.017)
# Days between 10 and 20 degrees	-0.004	-0.002
	(0.012)	(0.008)
# Days between 20 and 30 degrees	0.008	-0.002
	(0.008)	(0.004)
# Days between 30 and 40 degrees	0.007	0.000
	(0.006)	(0.002)
# Days between 40 and 50 degrees	0.004	0.001
	(0.004)	(0.003)
# Days between 50 and 60 degrees	0.006	0.002
	(0.004)	(0.004)
# Days between 70 and 80 degrees	-0.005	-0.006
	(0.004)	(0.005)
# Days between 80 and 90 degrees	0.018	0.011
	(0.023)	(0.023)
# Days above 90 degrees	0.076	0.111**
	(0.057)	(0.044)
Observations	20611	20611
Adjusted R^2	0.208	0.188
Mean	3.681	2.158
Panel B. Historically hotter counties (above-median average temperatures)		
# Days below 10 degrees	-0.045**	-0.006
	(0.018)	(0.020)
# Days between 10 and 20 degrees	0.023**	0.012
	(0.009)	(0.010)
# Days between 20 and 30 degrees	0.004	-0.003
	(0.002)	(0.002)
# Days between 30 and 40 degrees	0.001	-0.002
	(0.004)	(0.002)
# Days between 40 and 50 degrees	0.002	-0.002
	(0.002)	(0.002)
# Days between 50 and 60 degrees	-0.001	-0.004
	(0.004)	(0.003)
# Days between 70 and 80 degrees	-0.006**	-0.005**
	(0.003)	(0.002)
# Days between 80 and 90 degrees	-0.002	-0.005***
	(0.002)	(0.001)
# Days above 90 degrees	0.030	0.016
	(0.030)	(0.019)
Observations	21104	21104
Adjusted R^2	0.582	0.607
Mean	4.844	3.418

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. 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.

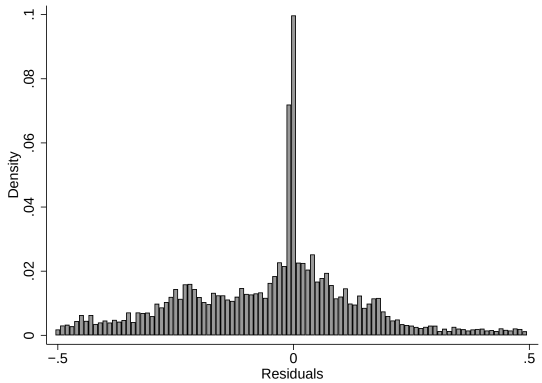
Table 5: Robustness to Including Two-Year Lags in Temperature Exposure

	(1)	(2)	(3)
	Outcome: Any prenatal hospitalization		
	Main specification in the subsample with two-year lags	Two-year lags only	Adding two-year lags to main specification
# Days below -3 SD temp	0.029		0.026
	(0.041)		(0.040)
# Days between -3 to -2 SD temp	-0.004		0.003
	(0.010)		(0.008)
# Days between -2 to -1 SD temp	0.006		0.006
	(0.004)		(0.004)
# Days between -1 to 0 SD temp	-0.002		-0.002
	(0.002)		(0.002)
# Days between 1 to 2 SD temp	-0.000		-0.002
	(0.004)		(0.004)
# Days between 2 to 3 SD temp	0.013**		0.022***
	(0.005)		(0.007)
# Days above 3 SD temp	0.091**		0.083**
	(0.034)		(0.033)
# Days below -3 SD temp (two-year lags), placebo		-0.076*	-0.079**
		(0.043)	(0.037)
# Days between -3 to -2 SD temp (two-year lags), placebo		0.014*	0.011*
		(0.008)	(0.007)
# Days between -2 to -1 SD temp (two-year lags), placebo		0.004	0.005
		(0.004)	(0.004)
# Days between -1 to 0 SD temp (two-year lags), placebo		-0.005*	-0.004
		(0.003)	(0.003)
# Days between 1 to 2 SD temp (two-year lags), placebo		-0.010***	-0.011***
		(0.002)	(0.003)
# Days between 2 to 3 SD temp (two-year lags), placebo		0.013	0.013
		(0.012)	(0.012)
# Days above 3 SD temp (two-year lags), placebo		0.003	0.038
		(0.039)	(0.043)
Observations	33154	33154	33154
Adjusted R^2	0.458	0.458	0.458
Mean	4.530	4.530	4.530

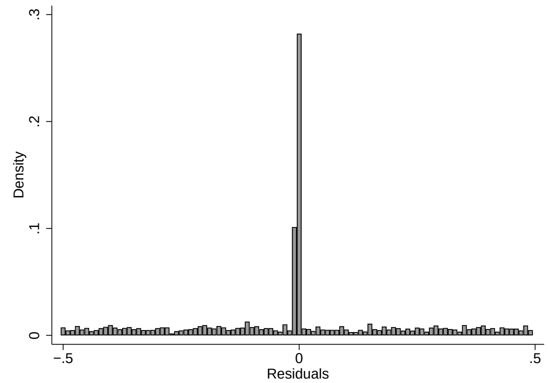
Source: HCUP SID merged with NOAA weather data

Notes: Column (1) reports regression coefficients (β_j) from equation (1) using the sub-sample of data for which we can calculate two-year lags of exposure (i.e., hypothetical exposure to temperature assuming that the child had been born two years prior to his/her actual month of birth). Column (2) shows results from models that only includes two-year lags of exposure and exclude actual exposure. Column (3) shows results from models that include both actual temperature exposure and two-year lags in temperature exposure. Robust standard errors, clustered by commuting zone, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions 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 series of indicators for terciles of 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.

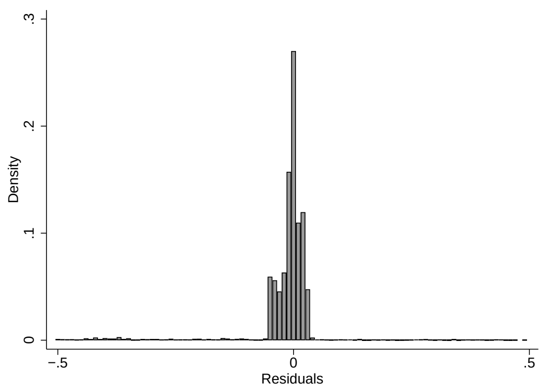
Appendix A. Appendix Figures



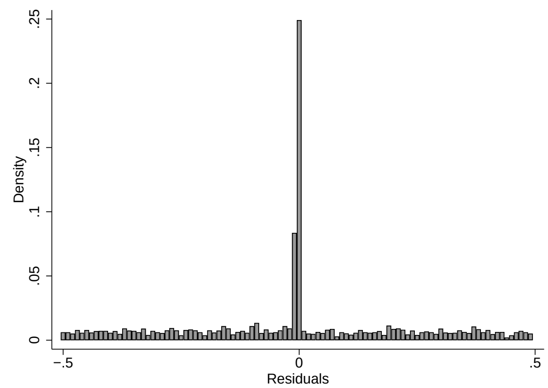
(a) Outcome: Days above 3 SD



(b) Outcome: Days between 0 to 1 SD



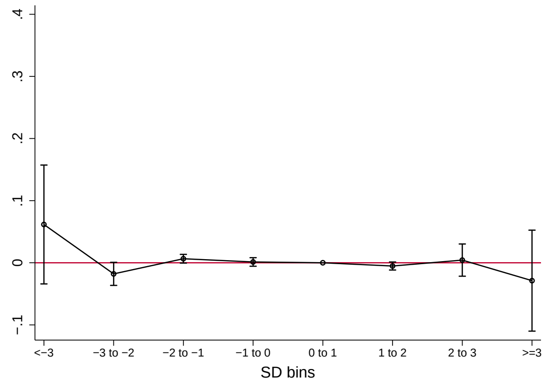
(c) Outcome: Days above 90^oF



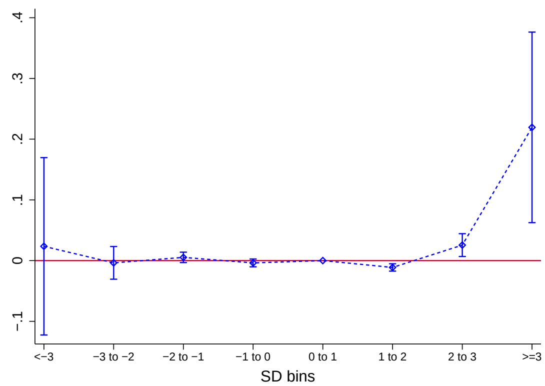
(d) Outcome: Days between 50 and 60^oF

Figure A.1: Histogram of the Distribution of the Residuals in Temperature After Conditioning on All Fixed Effects and Trends

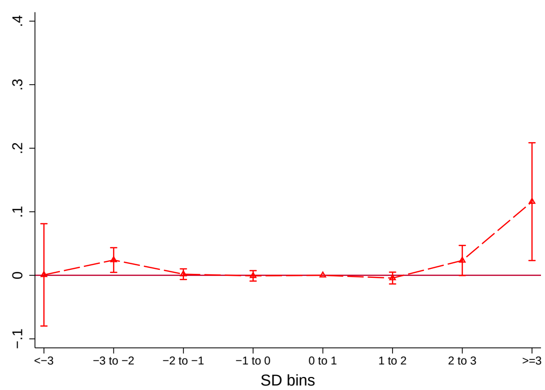
Notes: We compute residuals from a regression of the number of days in two SD bins and two absolute temperature bins during pregnancy on race×birth-county×birth-month fixed effects and birth-state×birth-year fixed effects and county×calendar month-specific quadratic trends.



(a) Trimester 1



(b) Trimester 2



(c) Trimester 3

Figure A.2: Effect of Temperature Deviations During Pregnancy on Maternal Hospitalization, by Trimester of Exposure

Notes: The figure plots regression coefficients for each SD bin with 95% confidence intervals separately for each trimester from a regression of any maternal hospitalization during pregnancy on SD temperature bins in each trimester. The regression 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 series of indicators for terciles of precipitation in each trimester. The outcome is rescaled by multiplying by 100. Standard errors are clustered by the commuting zone level. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used.

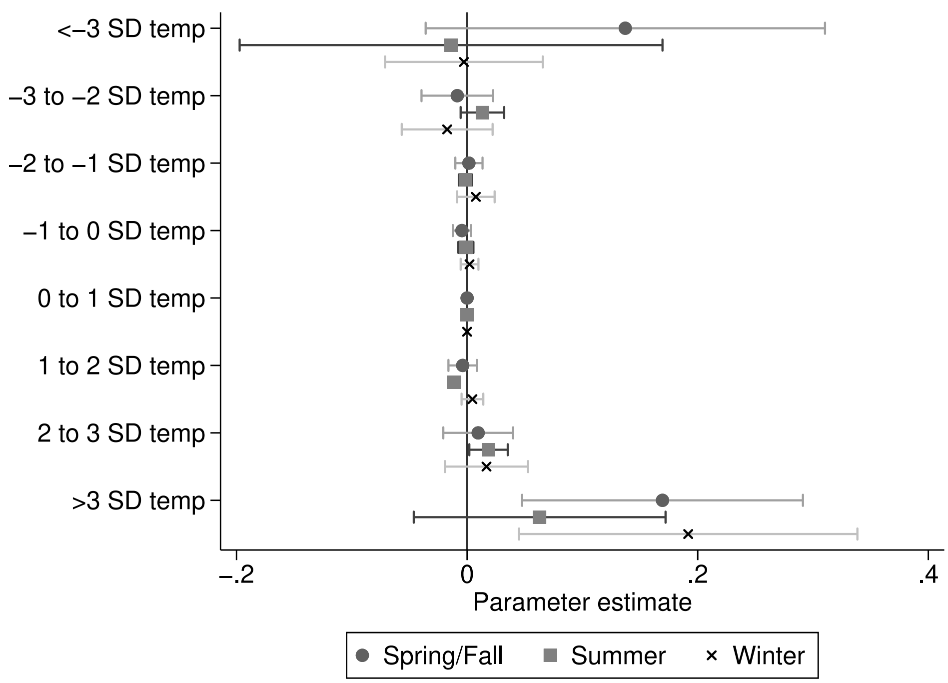


Figure A.3: Effect of Season-Specific Temperature Deviations During Pregnancy on Maternal Hospitalization

Notes: The figure plots regression coefficients on season-specific temperature deviations for each SD bin with 95% confidence intervals. Spring/Fall indicates temperature deviations in March, April, October, and November. Summer indicates temperature deviations in May to September. Winter indicates temperature deviations in December to February. The outcome is rescaled by multiplying by 100. Standard errors are clustered by the commuting zone level. The specification 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 indicators for terciles of precipitation in each trimester. 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 Exposure and Placebo Outcomes

	(1)	(2)	(3)	(4)
	White	Black	Hispanic	Other
Panel A. Maternal race				
# Days below -3 SD temp	0.332	-0.027	-0.244	-0.062
	(0.540)	(0.094)	(0.318)	(0.545)
# Days between -3 to -2 SD temp	-0.043	-0.003	0.047	-0.001
	(0.067)	(0.019)	(0.057)	(0.044)
# Days between -2 to -1 SD temp	0.011	0.003	0.023	-0.038
	(0.022)	(0.004)	(0.017)	(0.023)
# Days between -1 to 0 SD temp	-0.000	-0.003	0.038	-0.035*
	(0.025)	(0.003)	(0.026)	(0.019)
# Days between 1 to 2 SD temp	0.038	-0.001	0.003	-0.040*
	(0.025)	(0.005)	(0.022)	(0.024)
# Days between 2 to 3 SD temp	-0.118	0.007	0.100	0.011
	(0.092)	(0.010)	(0.079)	(0.036)
# Days above 3 SD temp	-0.060	0.003	-0.157	0.214
	(0.383)	(0.041)	(0.314)	(0.176)
Observations	9488	9488	9488	9488
Adjusted R^2	0.965	0.973	0.933	0.913
Mean	52.603	12.224	19.926	15.247
	Q1	Q2	Q3	Q4
Panel B. Median household income quartile for patient ZIP code				
# Days below -3 SD temp	-0.093	0.132	-0.222	0.183*
	(0.381)	(0.434)	(0.163)	(0.102)
# Days between -3 to -2 SD temp	-0.026	-0.001	0.055	-0.027
	(0.066)	(0.075)	(0.040)	(0.026)
# Days between -2 to -1 SD temp	0.022	0.005	-0.066	0.038
	(0.027)	(0.018)	(0.039)	(0.039)
# Days between -1 to 0 SD temp	0.008	-0.017	0.005	0.005
	(0.014)	(0.017)	(0.029)	(0.029)
# Days between 1 to 2 SD temp	0.009	-0.010	-0.015	0.015
	(0.024)	(0.021)	(0.019)	(0.021)
# Days between 2 to 3 SD temp	-0.003	0.076	-0.073	0.000
	(0.056)	(0.048)	(0.094)	(0.093)
# Days above 3 SD temp	-0.012	0.045	0.261	-0.293
	(0.254)	(0.268)	(0.274)	(0.277)
Observations	8345	8345	8345	8345
Adjusted R^2	0.963	0.926	0.921	0.986
Mean	23.271	23.206	23.390	30.133

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

Table B.2: Effects of Temperature Deviations During Pregnancy on the Number of Births

	Number of births
# Days below -3 SD temp	5.545
	(4.885)
# Days between -3 to -2 SD temp	-3.106
	(2.575)
# Days between -2 to -1 SD temp	0.433
	(0.504)
# Days between -1 to 0 SD temp	-0.121
	(0.251)
# Days between 1 to 2 SD temp	0.012
	(0.119)
# Days between 2 to 3 SD temp	-0.462
	(0.720)
# Days above 3 SD temp	0.729
	(1.610)
Observations	11204
Adjusted R^2	0.977
Mean	230.045

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients (β_j), from equation (1). The robust standard error, clustered by commuting zone, is in parenthesis. The regression controls for 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 series of indicators for terciles of precipitation in each trimester. We compute the number of births at the county-month level. * p<0.10, ** p<0.05, *** p<0.01.

Table B.3: Effects of Temperature Deviations on Primary Diagnoses Associated with Maternal Hospitalization

	ICD 640-649	ICD 640	ICD 641	ICD 642	ICD 643	ICD 644	ICD 645	ICD 646	ICD 647	ICD 648	ICD 649
# Days below -3 SD temp	0.028	-0.002	0.003	0.000	0.003	-0.001	-0.000	0.007	-0.001	0.017	0.003
	(0.042)	(0.002)	(0.006)	(0.005)	(0.005)	(0.027)	(0.002)	(0.010)	(0.005)	(0.018)	(0.004)
# Days between -3 to -2 SD temp	0.002	0.000	0.001	0.000	-0.000	-0.001	0.001*	0.000	-0.001**	-0.000	0.002**
	(0.007)	(0.000)	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)	(0.002)	(0.001)	(0.003)	(0.001)
# Days between -2 to -1 SD temp	0.003*	-0.000	0.001**	0.001**	0.001	-0.000	-0.000	0.001	0.000	-0.000	0.000
	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
# Days between -1 to 0 SD temp	-0.001	0.000	0.000	0.000	-0.001***	-0.001	0.000	-0.000	-0.000	0.001	0.001***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
# Days between 1 to 2 SD temp	-0.004	0.000	0.001**	0.001*	-0.001	-0.002	-0.000	-0.001	-0.000	-0.003**	0.002***
	(0.003)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
# Days between 2 to 3 SD temp	0.010*	-0.001	0.000	0.001	0.001	0.003	0.000	0.002	-0.001	0.003	0.001
	(0.006)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)
# Days above 3 SD temp	0.116***	0.000	-0.004	0.013**	0.007**	0.002	-0.000	0.042***	0.005	0.043**	0.007
	(0.030)	(0.003)	(0.008)	(0.006)	(0.004)	(0.015)	(0.001)	(0.013)	(0.004)	(0.020)	(0.005)
Observations	41715	41715	41715	41715	41715	41715	41715	41715	41715	41715	41715
Adjusted R^2	0.420	-0.061	0.042	0.059	0.102	0.202	0.007	0.138	0.040	0.274	0.112
Mean	4.086	0.043	0.226	0.231	0.243	1.203	0.008	0.668	0.094	1.258	0.111

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients (β_j) from equation (1). ICD codes 640-649 indicate "complications mainly related to pregnancy." The definition of each sub-category is as follows. ICD 640: Hemorrhage in early pregnancy; ICD 641: Antepartum hemorrhage abruptio placentae and placenta previa; ICD 642: Hypertension complicating pregnancy childbirth and the puerperium; ICD 643: Excessive vomiting in pregnancy; ICD 644: Early or threatened labor; ICD 645: Late pregnancy; ICD 646: Other complications of pregnancy not elsewhere classified; ICD 647: Infectious and parasitic conditions in the mother classifiable elsewhere but complicating pregnancy childbirth or the puerperium; ICD 648: Other current conditions in the mother classifiable elsewhere but complicating pregnancy childbirth or the puerperium; ICD 649: Other conditions or status of the mother complicating pregnancy, childbirth, or the puerperium. Robust standard errors, clustered by commuting zone, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions 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 series of indicators for terciles of 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.4: Effects of of Temperature Deviations on Secondary Diagnoses Associated with Maternal Hospitalization

	(1)	(2)	(3)	(4)
	Urinary	Digestive	Thrombocytopenia	Asthma
# Days below -3 SD temp	0.009	-0.002	-0.000	0.004
	(0.010)	(0.004)	(0.001)	(0.003)
# Days between -3 to -2 SD temp	0.001	0.002	-0.000	-0.002*
	(0.002)	(0.001)	(0.001)	(0.001)
# Days between -2 to -1 SD temp	0.000	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
# Days between -1 to 0 SD temp	0.000	-0.001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
# Days between 1 to 2 SD temp	-0.000	-0.001**	-0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.000)
# Days between 2 to 3 SD temp	0.002	-0.001	0.000	0.003***
	(0.002)	(0.001)	(0.000)	(0.001)
# Days above 3 SD temp	0.027**	0.007***	0.004*	0.003
	(0.013)	(0.003)	(0.002)	(0.004)
Observations	41715	41715	41715	41715
Adjusted R^2	0.107	-0.000	0.054	0.016
Mean	0.549	0.114	0.018	0.112

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients, β_j, from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. We use the data collapsed at the race×birth-county×birth-year-month level. Cell size weights are used. 'Urinary' indicates diagnosis codes for "Other Diseases Of Urinary System (ICD 9 codes 590-599)." 'Digestive' indicates diagnosis codes for "Other Diseases Of Digestive System (ICD 9 codes 570-579)." 'Thrombocytopenia' indicates diagnosis codes for unspecified thrombocytopenia (ICD 9 code 287.5). 'Asthma' indicates diagnosis codes for asthma (ICD 9 code 493). * p<0.10, ** p<0.05, *** p<0.01.

Table B.5: Effects of Absolute Temperatures During Pregnancy on Maternal Hospitalization

	(1)	(2)
	Prenatal hospitalization	
	Any	Emergency/urgent
# Days below 10 degrees	-0.011	-0.003
	(0.016)	(0.013)
# Days between 10 and 20 degrees	0.008	0.004
	(0.009)	(0.006)
# Days between 20 and 30 degrees	0.003	-0.004
	(0.004)	(0.003)
# Days between 30 and 40 degrees	0.002	-0.002
	(0.003)	(0.001)
# Days between 40 and 50 degrees	0.003	-0.000
	(0.002)	(0.002)
# Days between 50 and 60 degrees	0.000	-0.003
	(0.003)	(0.003)
# Days between 70 and 80 degrees	-0.006***	-0.005***
	(0.001)	(0.002)
# Days between 80 and 90 degrees	-0.002	-0.006***
	(0.003)	(0.001)
# Days above 90 degrees	0.033	0.021
	(0.028)	(0.019)
Observations	41715	41715
Adjusted R^2	0.474	0.500
Mean	4.530	3.078

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. 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 Temperature Deviations During Pregnancy on Maternal Hospitalization, by State

	(1)	(2)	(3)	(4)	(5)	(6)
	Arizona		New York		Washington	
	Any	Emergency/urgent	Any	Emergency/urgent	Any	Emergency/urgent
# Days below -3 SD temp	-0.091	-0.138	0.097	0.094**	-0.011	-0.009
	(0.284)	(0.162)	(0.079)	(0.032)	(0.022)	(0.020)
# Days between -3 to -2 SD temp	-0.034	-0.020	-0.007	-0.003	0.016**	0.004
	(0.104)	(0.063)	(0.009)	(0.008)	(0.006)	(0.004)
# Days between -2 to -1 SD temp	0.017	0.008	0.002	-0.002	0.003	-0.004
	(0.019)	(0.018)	(0.002)	(0.004)	(0.003)	(0.003)
# Days between -1 to 0 SD temp	-0.001	-0.002	-0.002	-0.004	0.001	-0.007*
	(0.026)	(0.016)	(0.002)	(0.002)	(0.004)	(0.004)
# Days between 1 to 2 SD temp	-0.003	-0.004	-0.007**	-0.010***	-0.002	-0.010
	(0.012)	(0.011)	(0.003)	(0.002)	(0.008)	(0.007)
# Days between 2 to 3 SD temp	-0.086	-0.096	0.015**	0.014**	0.018	0.004
	(0.120)	(0.098)	(0.006)	(0.006)	(0.014)	(0.006)
# Days above 3 SD temp	0.000	0.000	0.135***	0.098***	0.031	-0.001
	(.)	(.)	(0.033)	(0.020)	(0.057)	(0.055)
Observations	3453	3453	28958	28958	9304	9304
Adjusted R^2	0.391	0.389	0.512	0.534	0.227	0.205
Mean	4.027	3.261	4.867	3.331	3.417	1.779

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. 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 Absolute Temperatures During Pregnancy on Maternal Hospitalization, by State

	(1)	(2)	(3)	(4)	(5)	(6)
	Arizona		New York		Washington	
	Any	Emergency/urgent	Any	Emergency/urgent	Any	Emergency/urgent
# Days below 10 degrees	0.000	0.000	-0.013	-0.003	-0.018	-0.034
	(.)	(.)	(0.017)	(0.014)	(0.046)	(0.024)
# Days between 10 and 20 degrees	1.311**	1.041**	0.009	0.006	-0.005	-0.012
	(0.497)	(0.333)	(0.011)	(0.007)	(0.017)	(0.020)
# Days between 20 and 30 degrees	0.373**	0.222*	0.002	-0.004	0.013	-0.002
	(0.118)	(0.111)	(0.005)	(0.003)	(0.008)	(0.006)
# Days between 30 and 40 degrees	0.095	0.044	0.002	-0.001	0.008	-0.001
	(0.068)	(0.064)	(0.004)	(0.002)	(0.005)	(0.003)
# Days between 40 and 50 degrees	0.011	0.005	0.005	0.001	0.001	0.001
	(0.047)	(0.045)	(0.003)	(0.002)	(0.005)	(0.002)
# Days between 50 and 60 degrees	0.021	0.013	-0.001	-0.005	-0.001	0.002
	(0.020)	(0.015)	(0.004)	(0.003)	(0.005)	(0.003)
# Days between 70 and 80 degrees	0.006	-0.006	-0.006***	-0.005***	0.003	0.004
	(0.030)	(0.026)	(0.001)	(0.002)	(0.009)	(0.010)
# Days between 80 and 90 degrees	0.011	-0.001	-0.004	-0.007***	-0.024	-0.008
	(0.021)	(0.025)	(0.003)	(0.001)	(0.029)	(0.006)
# Days above 90 degrees	0.028	0.006	0.102***	0.071**	1.378***	0.986***
	(0.044)	(0.043)	(0.012)	(0.027)	(0.137)	(0.118)
Observations	3453	3453	28958	28958	9304	9304
Adjusted R^2	0.394	0.390	0.512	0.534	0.227	0.205
Mean	4.027	3.261	4.867	3.331	3.417	1.779

Source: HCUP SID merged with NOAA weather data
Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. 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.8: Effects of Temperature Deviations During Pregnancy on Maternal Hospitalization, Robustness to Including Different Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# Days below -3 SD temp	0.069	0.056*	0.067	0.031	0.037	0.023	0.023
	(0.041)	(0.032)	(0.041)	(0.053)	(0.039)	(0.042)	(0.042)
# Days between -3 to -2 SD temp	0.001	0.001	-0.000	0.002	0.000	-0.001	-0.001
	(0.008)	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)	(0.008)
# Days between -2 to -1 SD temp	0.011**	0.012***	0.011**	0.006*	0.005**	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
# Days between -1 to 0 SD temp	0.003*	0.002	0.003*	0.007**	0.000	-0.002	-0.002
	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
# Days between 1 to 2 SD temp	0.005**	0.004**	0.005**	0.006	-0.002	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
# Days between 2 to 3 SD temp	-0.004	0.009	-0.003	-0.015	0.010	0.014**	0.014**
	(0.009)	(0.010)	(0.009)	(0.009)	(0.006)	(0.005)	(0.005)
# Days above 3 SD temp	0.086***	0.078**	0.090***	0.086***	0.103***	0.101***	0.101***
	(0.031)	(0.035)	(0.032)	(0.029)	(0.034)	(0.033)	(0.033)
Observations	41715	41715	41715	41715	41715	41715	41715
Adjusted R^2	0.455	0.315	0.455	0.467	0.474	0.474	0.474
Mean	4.530						
Precipitation	Y	Y	Y	Y	Y	Y	Y
Race×birth-county×birth-month fixed effects	Y		Y	Y	Y	Y	
Race×birth-county×calendar-month fixed effects							Y
Birth-county×birth-month fixed effects		Y					
Birth-state×birth-year fixed effects	Y	Y	Y		Y	Y	Y
Birth-county×birth-year fixed effects				Y			
ZIP code income quartiles		Y	Y	Y	Y	Y	Y
Linear birth-county×birth-month trends					Y		
Quadratic birth-county×birth-month trends						Y	Y

Source: HCUP SID merged with NOAA weather data

Notes: This table reports how the regression coefficients (β_j) from equation (1) change as we add in different sets of control variables. Robust standard errors, clustered by commuting zone, are in parentheses. The outcome is rescaled by multiplying by 100. Precipitation indicates a series of indicators for terciles of precipitation in each trimester. 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.9: Robustness to Including One-Year Lags or One-Year Leads in Temperature Exposure

	(1)	(2)	(3)	(4)
	Any prenatal hospitalization			
	Main specification in the subsample with one-year lags	Adding one-year lags	Main specification in the subsample with one-year leads	Adding one-year leads
# Days below -3 SD temp	0.034	0.048	0.019	0.029
	(0.044)	(0.046)	(0.044)	(0.044)
# Days between -3 to -2 SD temp	0.000	-0.002	-0.001	0.001
	(0.008)	(0.010)	(0.009)	(0.008)
# Days between -2 to -1 SD temp	0.002	0.003	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.003)
# Days between -1 to 0 SD temp	-0.001	-0.002	-0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
# Days between 1 to 2 SD temp	-0.005	-0.002	-0.006**	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
# Days between 2 to 3 SD temp	0.010*	0.010	0.014**	0.021***
	(0.005)	(0.006)	(0.006)	(0.006)
# Days above 3 SD temp	0.107***	0.114**	0.106***	0.087***
	(0.031)	(0.044)	(0.035)	(0.032)
# Days below -3 SD temp, placebo		0.028		0.034
		(0.039)		(0.021)
# Days between -3 to -2 SD temp, placebo		-0.012		-0.002
		(0.008)		(0.004)
# Days between -2 to -1 SD temp, placebo		-0.004		-0.004
		(0.003)		(0.003)
# Days between -1 to 0 SD temp, placebo		-0.004*		0.001
		(0.003)		(0.002)
# Days between 1 to 2 SD temp, placebo		0.003		-0.008***
		(0.003)		(0.003)
# Days between 2 to 3 SD temp, placebo		-0.006		0.009
		(0.007)		(0.007)
# Days above 3 SD temp, placebo		0.024		-0.040*
		(0.060)		(0.020)
Observations	37452	37452	39073	39073
Adjusted R^2	0.468	0.469	0.464	0.464
Mean	4.530	4.530	4.530	4.530

Source: HCUP SID merged with NOAA weather data

Notes: One-year lags refer to hypothetical exposure assuming a child had been born one year prior to his/her actual month of birth, while one-year leads refer to hypothetical exposure assuming a child had been born one year after his/her actual month of birth. Column (1) and (3) report regression coefficients (β_j) from equation (1) using sub-samples for which we can calculate one-year lags and one-year leads in exposure, respectively. Columns (2) and (4) additionally include one-year lags and leads in temperature exposure, respectively. Robust standard errors, clustered by commuting zone, are in parentheses. Each outcome is rescaled by multiplying by 100. All regressions 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 indicators for terciles of 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.10: Effects of Temperature Deviations During Pregnancy on Maternal Hospitalization, Robustness to Including AQI Controls

	Any prenatal hospitalization	Emergency/urgent
Panel A. Main specification in the subsample with AQI measures		
# Days below -3 SD temp	0.034	0.024
	(0.046)	(0.027)
# Days between -3 to -2 SD temp	-0.007	-0.007
	(0.011)	(0.006)
# Days between -2 to -1 SD temp	0.005**	-0.000
	(0.002)	(0.004)
# Days between -1 to 0 SD temp	-0.001	-0.006***
	(0.002)	(0.002)
# Days between 1 to 2 SD temp	-0.004*	-0.009***
	(0.002)	(0.002)
# Days between 2 to 3 SD temp	0.010*	0.010
	(0.005)	(0.007)
# Days above 3 SD temp	0.107***	0.071***
	(0.034)	(0.025)
Observations	26967	26967
Adjusted R^2	0.532	0.572
Mean	4.574	3.151
Panel B. Adding AQI measures		
# Days below -3 SD temp	0.032	0.023
	(0.047)	(0.028)
# Days between -3 to -2 SD temp	-0.004	-0.006
	(0.011)	(0.006)
# Days between -2 to -1 SD temp	0.005*	-0.000
	(0.002)	(0.003)
# Days between -1 to 0 SD temp	-0.001	-0.005**
	(0.002)	(0.002)
# Days between 1 to 2 SD temp	-0.004*	-0.009***
	(0.002)	(0.002)
# Days between 2 to 3 SD temp	0.010**	0.010
	(0.005)	(0.007)
# Days above 3 SD temp	0.107***	0.070***
	(0.034)	(0.024)
Observations	26967	26967
Adjusted R^2	0.533	0.572
Mean	4.574	3.151

Source: HCUP SID merged with NOAA weather data

Notes: This table reports regression coefficients (β_j) from equation (1). Robust standard errors, clustered by commuting zone, 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 series of indicators for terciles of precipitation in each trimester. In panel B, we include a series of indicators for AQI categories ("good," "moderate," "unhealthy for sensitive groups," "very unhealthy," with "hazardous" as a reference group) in the model. 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.