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Maybe Next Month? Temperature Shocks and Dynamic Adjustments in Birth Rates

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Abstract

We estimate the effects of temperature shocks on birth rates in the United States between 1931 and 2010. We find that days with a mean temperature above 80°F cause a large decline in birth rates 8 to 10 months later. Unlike prior studies, we demonstrate that the initial decline is followed by a partial rebound in births over the next few months, implying that populations mitigate some of the fertility cost by shifting conception month. This shift helps explain the observed peak in late-summer births in the United States. We also present new evidence that hot weather most likely harms fertility via reproductive health as opposed to sexual activity. Historical evidence suggests that air conditioning could be used to substantially offset the fertility costs of high temperatures.

Keywords

Fertility; Birth rates; Birth seasonality; Temperature

Introduction

The strong seasonality in births across many countries suggests that ambient temperature may have a sizable influence on fertility, although the extent of the causal relationship is not well documented. In the most convincing temperature-fertility study to date, Lam and Miron (1996) found that atypically warm months led to a decline in births 9 to 10 months later. Our study advances our understanding of temperature's impact on fertility in two ways. First, we explore whether individuals mitigate fertility costs by shifting conceptions to later months.

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Second, we investigate whether the critical exposure period occurs *before* or *at* the estimated time of conception, shedding light on the channel through which high temperatures affect birth rates. The potential for climate change to increase the frequency of extreme temperatures adds to this study's topical importance.[1]

We document the effect of temperature on monthly birth rates for each state in the United States between 1931 and 2010. To test for potential shifts in conception month, our empirical model allows temperature to affect birth rates up to 24 months from the time of the shock. Without accounting for this dynamic response, short-run effects will overstate the effect on cumulative birth rates. Similar to previous research, we estimate the effects of *unusual* temperatures so as to avoid seasonal confounders, such as holidays, that might have an independent effect on fertility. However, we model the temperature-fertility response function with more flexibility than previous research to account for differential effects at the extremes of the temperature distribution.

Our estimates indicate that hot weather causes a significant decline in birth rates 8 to 10 months later. One additional "hot day" with a mean temperature above 80°F,[2] relative to one day between 60°F and 70°F, causes a 0.4 % decrease in birth rates nine months later. Because we use the daily *mean* temperature, nearly 75% of these hot days actually have a maximum temperature above 90°F. After the initial decline, birth rates partially rebound over the next few months; the increase in births in months 11, 12, and 13 offsets approximately 32 % of the decline in births in months 8, 9, and 10. Cold temperatures, such as days with a mean temperature below 30°F, have relatively little impact on birth rates. We also document a significant dampening in the temperature–fertility response function beginning in the 1960s and show that residential access to air conditioning explains one-third of this dampening.

Finally, we provide novel evidence regarding the critical exposure period in relation to the timing of conception. For this analysis, we use detailed natality data (1969–2004) with information on the date of the mothers' last normal menses. These data are limited in that they encompass only those conceptions that survive to birth. We find that temperature at the time of conception has no discernable effect on conceptions. Thus, temperature is unlikely to have an *immediate* impact on sexual activity (at least to an extent that counters any immediate impact on reproductive health or contraceptive use). However, we find that hot weather does indeed reduce conceptions when exposure occurs two weeks *before* the estimated time of conception. This finding indicates that temperature has a latent effect on conception chances, which is more easily explained by a decline in reproductive health as opposed to some delayed effect on sexual activity.

[1]Recent research has demonstrated that unexpected temperature shocks affect a variety of socioeconomic outcomes, including mortality, labor supply, and income. For mortality, see Barreca (2012), Barreca et al. (2016), Deschenes and Greenstone (2011), and Deschenes and Moretti (2009). For infant health, see Deschenes et al. (2009). For income, see Deryugina and Hsiang (2014). For labor supply, see Graff Zivin and Neidell (2014). See Dell et al. (2014) for a summary of this literature.

[2]Throughout the article, "above 80°F" indicates mean temperature above 80°F.

Conceptual Framework of the Dynamic Temperature–Fertility Relationship

For a nonpregnant female, the chance of conceiving in any given (reproductive) cycle, henceforth referred to as *conception probability*, is mainly a function of three factors: (1) each partner's reproductive health, (2) their coital frequency, and (3) contraceptive use. With regard to reproductive health, prior work has found that spermatogenesis and the menstrual cycle, including the ovulation rate, differ by season but that factors other than temperature may be affecting these seasonal patterns (Ellison et al. 2005; Levine 1991; Rojansky et al. 1992; Svartberg et al. 2003). However, compelling experimental evidence suggests that high temperatures negatively affect reproductive health of nonhuman mammals, especially males (Hansen 2009).

The evidence on the relationship between temperature and sexual activity is limited to seasonal relationships, which are likely influenced by factors other than temperature (Levin et al. 2002; Rodgers et al. 1992; Udry and Morris 1967). For example, temperature shocks could affect coital frequency by raising the cost of physical activity. Temperature may also affect time use and, in turn, affect mixing rates among potential sexual partners, especially if they spend more time indoors (Graff Zivin and Neidell 2014). Individuals may time coitus based on expectations about future weather and their preferences to maximize infant health outcomes or minimize pregnancy costs (Rodgers and Udry 1988). Given our research design, our estimates incorporate this channel only to the extent that current temperature shocks affect expectations about future shocks.

Temperature might also influence fertility via changes in contraceptive effectiveness. Pharmaceuticals, including hormonal birth control pills, experience diminished effectiveness when stored at temperatures outside of manufacturer guidelines (see, e.g., Baystate Health 2014). For example, the manufacturer of a commonly prescribed hormonal birth control pill, Beyaz, provides clear instructions that it should be stored at room temperature (77°F) (see, e.g., Bayer HealthCare Pharmaceuticals 2010). The effectiveness of condoms also deteriorates when stored at high temperatures (Gerofi and Sorensen 2016). Failure of contraceptives resulting from high temperatures, however, would lead to increased births, which is opposite of our findings.

Temperature could also influence fertility through more indirect channels, such as income, although the effect on conception probabilities may be delayed. Temperature could affect transmission of diseases, such as influenza (Barreca and Shimshack 2012; Lowen and Steel 2014; Shaman and Kohn 2009), which could alter reproductive health.

Any change in conception probabilities in one cycle can affect the number of conceptions in future cycles via changes in the susceptible population and not necessarily through any concerted change in behavior. Let the temperature shock in cycle t cause conceptions in that cycle to fall by Δ_t. In the simple case where the temperature shock has no effect on future conception probabilities and all individuals have identical positive conception probabilities, the change in conceptions in the subsequent cycle $(t + 1)$ would be $\Delta_t p_{t+1}$, where p_{t+1} is the conception probability in cycle $t + 1$. The increase in conceptions would be $p_{t+2}(1 - p_{t+1})\Delta_t$ in cycle $t + 2$, $p_{t+3}(1 - p_{t+2})(1 - p_{t+1})\Delta_t$ in cycle $t + 3$, and so on. Given that Δ_t and $p_{t'}$ (for all

$t' > t$) are positive, we expect an increase (or rebound) in conceptions in the cycles after cycle t. With constant conception probabilities, the cumulative rebound would asymptotically approach Δ_t.[3]

The rebound could be nonmonotonic in the case of time-varying conception probabilities due to credit constraints, seasonal changes in contraceptive use, or preferences for conceiving in certain calendar months. Conversely, declining reproductive health with age could lead to a smaller cumulative rebound.[4] If the temperature shock has an impact on future conception probabilities ($dp_{t+1} \neq 0$), the change in conceptions at $t + 1$ would be $\Delta_t p_{t+1} + S_{t+1} dp_{t+1}$, where S_{t+1} is the susceptible population, and dp_{t+1} is the change in the conception probability due to the temperature shock. For example, the shock could cause lasting health complications ($dp_{t+1} < 0$) or an increase in coital frequency ($dp_{t+1} > 0$). Given that the sign and magnitude of dp_{t+1} is uncertain, the net effect on conceptions in cycle $t + 1$ is ambiguous.[5]

Because of the limited data on conceptions, studies have estimated the effects of temperature in a given calendar month on realized births approximately nine calendar months later (Lam and Miron 1991, 1996; Lam et al. 1994; Seiver 1985, 1989). Only Lam and Miron (1996) (hereafter LM) and Seiver (1989) relied on variation in atypical temperatures, thereby controlling for seasonal confounders. Neither of these studies comprehensively investigated the importance of dynamic adjustments, which is a key contribution of our work.[6] Seiver (1989) used data for the United States between 1950 and 1960, correlating atypical monthly temperatures with the birth rate 9 months later within each state. LM followed a similar approach to Seiver but used data from the United States between 1942 and 1988. LM's core model allows temperature to affect birth rates 9 to 10 months later. Both Seiver's and LM's models are estimated separately by state, so statistical precision and ability to flexibly control for time-varying confounders is limited. And, these studies imposed relatively strong functional form assumptions on the temperature-fertility relationship: Seiver imposed a linear effect in monthly mean temperature, and LM used a quadratic in monthly mean temperature. Our model allows the temperature-fertility relationship to be estimated with greater flexibility to account for differential effects across the full distribution of daily temperatures.

Data

Natality Data

Birth counts are available at the state-by-month level from 1931 through 2010. The data come from three sources. We compile state-by-month birth counts from historical Vital

[3]With constant conception probabilities, the cumulative rebound in conceptions as of cycle $t + m$ would be $\sum_1^m p(1-p)^{m-1}\Delta_t$. If p = 10 %, the rebound would be 27 % after 3 months and 72 % after 12 months.

[4]Indeed, we find that the rebound is smaller for mothers older than 35 years (see Online Resource Table S1).

[5]See Lam et al. (1994) for a more formal fertility model.

[6]Although LM noted testing for effects at 7, 8, and 11 months, these estimates are statistically insignificant and are dropped from the model. Seiver (1989) tested for a rebound in births after month 9 for the period 1950–1960, but only a test of joint significance is reported in the text. Seiver concluded that "the making up effect is essentially complete after 7 months" (p. 246). The confidence interval on this statistical test (not reported) is potentially large because the model is estimated separately by state and the data span 11 years.

Statistics reports for 1931–1967,[7] from machine-readable Natality Files for years 1968–2004,[8] and from the Centers for Disease Control and Prevention (CDC) online National Vital Statistics System for 2005–2010. The monthly birth counts are defined by state of residence except for the 1931–1941 period, when only state of occurrence is available.[9]

We define state-by-month birth rates as the number of births in a given state-month averaged over the days in that month divided by the total population in 100,000s for that state and year. For 1931–1968, we estimate state-by-year populations by linearly interpolating between decennial censuses. For 1969–2010, we use state-by-year population estimates from the National Cancer Institute (2013). Our outcome of interest is the log of the birth rate for the total population, although our results are robust to using birth rates in levels, the female population between ages 15 and 44 in the denominator, or log of total births without adjusting for population size. The natality data have information on date of last menses, which we use to better approximate date of conception in a secondary set of analyses.

Weather Data

The primary weather data come from the National Climatic Data Center's Global Historical Climatology Network (GHCN), which has daily station information on minimum temperature, maximum temperature, and precipitation (Menne et al. 2012). The GHCN also has geographic coverage across the continental United States over our sample period and includes an impressive number of weather stations: 2,206 stations in 1930 and 4,969 stations in 2010 consistently reported daily weather conditions.[10]

We construct state-by-month weather measures from the station-day observations as follows. First, we aggregate the station-day data to the county-month level using the square of the inverse distance as weights, where we measure distance from the weather station to the county centroid for stations within 100 miles. Next, we average the county-month measures to the state-month level using county-year population estimates as weights.[11]

We have humidity data from a separate data source, the Global Summary of the Day files. We opt to control for specific humidity, which is reported in grams of water vapor per kilogram of air (g/kg) (for a discussion on the merits of using specific humidity over other measures, see Barreca 2012). The humidity variable has poor coverage prior to 1945, so we control for humidity only as a robustness check. To the extent that humidity and temperature are naturally correlated, our temperature estimates incorporate some of the effects of humidity.

[7]The first year that birth counts are available at the state-month level is 1931. South Dakota and Texas were not part of the Vital Statistics sample until 1932 and 1933, respectively. Monthly data with finer geographic detail, such as county, are not available prior to 1968.

[8]The first year of the natality data is 1968. In the earlier years, some states' data are 50 % samples, so we weight these births by 2. The public-use natality files do not report state of residence after 2004. Therefore, we rely on the CDC online National Vital Statistics System for the years 2005–2010.

[9]State of residence is the preferred measure given that migration could be endogenous to temperature.

[10]To address measurement error, we exclude stations for a given year-month if they are missing temperature readings more than 10 days in the year or 2 days in any given calendar month.

[11]We linearly interpolate county population between the decennial censuses up until 1968. Starting in 1969, we use county population estimates from the National Cancer Institute (2013).

Summary Statistics

Table 1 summarizes the birth rates and key temperature variables for the continental United States and by census region over the entire sample period (1931–2010). These statistics are means-calculated using the state-year population as weights. There were, on average, approximately 4.7 daily births per 100,000 residents during our sample period. The *mean* daily temperature was above 80°F approximately 2.3 days per month, on average. For days with a mean temperature above 80°F, close to 75 % have a maximum above 90°F. As such, we emphasize that a mean daily temperature above 80°F is “very hot.”

Birth rates are lowest in northeastern states and highest in southern states. The average temperature is above 80°F approximately 4.7 days per month in the South, compared with only 0.6 days in the Northeast. Although high temperature days and birth rates are positively correlated across regions, this positive relationship cannot be used to infer causal effects because many other socioeconomic factors, such as poverty rates, also correlate with climate. These omitted variables highlight the importance of using within-state changes in temperature realizations to identify causal impacts.

Seasonality in birth rates varies considerably across region. Figure 1 presents the mean of the log birth rate, by census region, over our sample period. In every region, birth rates peak in September, suggesting that individuals are most likely to conceive between December and January. Seasonality is greatest in the South, where September birth rates are 15 % higher than April birth rates. The differences across regions also suggest that temperature plays a role in the timing of births, given that the South is generally warmer than other regions of the United States. Other seasonal factors, such as demand for agricultural labor, could also account for cross-region differences in birth seasonality. Our empirical model mitigates this type of concern by including state-by-calendar-month fixed effects. Moreover, the fact that the seasonality is greatest in the South suggests that variation in the upper end of the temperature distribution might be a strong predictor of birth seasonality, a feature we incorporate into our empirical model.

Methodology

To identify the effect of temperature fluctuations on the birth rate, our model relies on random variation in the temperature distribution for a given state and calendar month. To begin, we estimate the following panel regression model that follows the specification of Barreca (2012):

$$\begin{aligned} Y_{st} = \sum_{j}^{J} \sum_{k}^{K} \beta_k^j \mathbf{TEMP}_{s,t-k}^j + \sum_{k}^{K} \gamma_k \mathbf{X}_{s,t-k} + \alpha_{sm} + \delta_t + \theta_{sy} + \left(\pi_{sm}^1 \times t\right) \\ + \left(\pi_{sm}^2 \times t^2\right) + e_{st}, \end{aligned} \tag{1}$$

where Y is the log of the birth rate in state s at year-month t. $\mathbf{X}$ is a vector of precipitation controls.[12] α_{sm} is a state-by-calendar-month fixed effect to help ensure that our model is

[12]We control for the fraction of days in the month $t-k$ with between 0.01 and 0.50 inches and more than 0.50 inches. The omitted category is the fraction of the month with no precipitation.

identified from the presumed random annual fluctuation in the distribution of temperatures in a given state and calendar month. These fixed effects adjust for permanent unobserved state-by-calendar-month determinants of the birth rate, such as patterns of seasonal employment. Year-by-calendar-month fixed effects (δ_t) control for time-varying factors that are common to all states, such as national business cycles. State-by-calendar-month quadratic time trends (π_{sm}) help mitigate potential biases from convergence in seasonality across states over time. Further, these controls help account for trends in local factors that affect fertility (possibly in a seasonal manner), such as air pollution. State-by-year fixed effects (θ_{sy}) help account for temperature changes that may correlate spuriously over time with demographic changes at the state level, such as immigration. We cluster standard errors at the state level to allow for unrestricted serial correlation in the errors within states over time. We weight by state-year population in the preceding year ($y - 1$) to improve precision and avoid endogenous weights. The unweighted estimates (not reported) are nearly identical.

TEMP is a vector of J temperature bins that captures the distribution of daily average temperatures in state s in month $t - k$. The bins represent the fraction of each month when daily mean temperatures (in degrees Fahrenheit) are <30, 30–40, 40–50, 50–60, 70–80, >80, with 60–70 as the omitted category. This type of specification is now common in studies examining temperature effects (Dell et al. 2014). The possibility of a dynamic relationship between birth rates and temperatures is introduced by allowing birth rates in month t to be affected by the temperature bins for up to 25 months inclusive of month t (denoted by the index $k = 0, 1, 2, \ldots, 24$). We also estimate impacts on births 1 to 3 months prior (denoted by the index $k = -3, -2, -1$) as a placebo check because the temperatures were realized after delivery and should not affect prior birth rates.

As a robustness check, we also test for impacts using a polynomial spline in the daily mean temperature, with knots at (degrees Fahrenheit) 10, 30, 50, 70, and 90. We use diurnal temperatures in place of daily mean temperatures as a test of intraday temperature extremes. For example, a day with a maximum of 90 and a minimum of 80 might affect fertility outcomes differently than a day with a maximum if 100 and a minimum of 70, despite both having the same daily mean temperature. We present results controlling for humidity in Online Resource 1.

Although the qualitative *dynamic* relationship is robust to varying the fixed effects, the *levels* of the estimates are sensitive to such modifications. Without the state-by-year fixed effects, the estimates are systematically shifted in the negative direction, including the placebo months (−3, −2, and −1) when the weather realization occurred after the birth month. This suggests a spurious time series correlation between temperatures and birth rates. An examination of the regional trends supports this assertion (see Online Resource 1, Fig. S1). For this reason, we opt for the model with state-year fixed effects as our preferred specification.

We can dismiss the concern that the identifying variation in our model is coming almost entirely from a select group of states. In Online Resource 1, Fig. S2, we regress the variable for >80°F days on the full set of controls in our model with the exception of precipitation or other temperature variables. For each state, we examine the annual average of the absolute residuals from this regression for the full sample period (1931–2010). Southern states expectedly account for more of the residual variation. However, the difference is not overwhelming: northeastern states have average absolute residuals roughly one-third the magnitude of southern states.

Results

Core Results

Figure 2, panel a, reports the effects of one >80°F day relative to one day in the 60°F to 70°F temperature bin on the log birth rate across the full set of exposure months using our core empirical model (Eq. (1)). We control for the full set of temperature bins, although we focus on the effects of >80°F days in panel a. The estimates indicate that each additional >80°F day causes birth rates to fall by approximately 0.06 % eight months later, 0.40 % nine months later, and 0.21 % ten months later; all three effects are statistically significant at the 5 % level. The fact that the largest effect is observed at 9 months is consistent with hot days having a relatively immediate impact on conception probabilities. The magnitude of the estimates is meaningful: the effect size at month 9 implies an average reduction of 1,150 fewer births across the whole United States for each >80°F day over our sample period.[13]

The magnitude of the coefficient at month 10 provides suggestive evidence that the critical exposure period is just *before* the time of conception. Assuming a 40-week gestational length, any immediate impact on conceptions should manifest approximately 260–270 days (i.e., eight or nine calendar months) later because most fertile days fall between 10 and 20 days after the start of the menses (Fehring et al. 2006; Wilcox et al. 1995). If the critical exposure period was around the time of conception, we should see virtually no decline in births at month 10 because few pregnancies last longer than 41 weeks.[14] Instead, the coefficient at month 10 is approximately one-half the magnitude of the month 9 coefficient (0.0021 vs. 0.0040). It is possible that the fall in births was disproportionately made up of births with atypically long gestational lengths, although we do not find evidence to support this hypothesis using natality data from a more recent period (see Online Resource Table S1). More plausibly, exposure to high temperatures has a delayed effect on conception rates, something that we investigate more closely in the section, Investigating the Critical Week of Exposure.

We also document a sizable rebound in births at 11, 12, and 13 months after the temperature shock. For example, one >80°F day causes a 0.10 % increase in births 12 months later. Note that the cumulative effect of a temperature shock over months 8–10 is a decrease of 0.0067 log points, whereas births rebound by 0.0021 log points over months 11–13 (jointly statistically significant) and an additional 0.0012 log points over months 14–23 (jointly statistically significant). The majority of the secondary rebound (0.0008 log points) occurs between months 19 and 21 (jointly statistically significant), suggesting that some people may have preferences for conceiving or engaging in sexual activity in certain calendar

[13]The average number of monthly births over our sample period is 295,000.

[14]Theoretically, we could observe an *increase* in births in month 10 if the affected population becomes susceptible to conceiving in the month immediately following the temperature shock.

months. In sum, the rebound in months 11–13 offsets 31 % (0.0021/ 0.0067) of the decline in months 8–10, and the rebound in months 14–24 offset an additional 18 % (0.0012/0.0067), bringing the cumulative rebound to nearly 50 %.

The coefficients on months 0 and 1 suggest that hot weather reduces gestational lengths. One >80°F day causes a statistically significant increase in birth rates in the exposure month (month 0) and a decrease one month later (month 1), indicative of a forward shift in the timing of some births. This evidence of shortened gestational lengths has been found in epidemiological studies, although our finding is compelling given that our sample covers every state and a longer period than previous studies (Avalos et al. 2017; Basu et al. 2010, 2016). Importantly, our estimates for the placebo months (−3, −2, −1) are statistically insignificant and near 0. Thus, our model appears to be free of biases from spurious time trends.

Figure 2, panel b, presents the temperature-fertility response function linking birth rates in month t with daily temperatures in month $t-9$ to explore the effect of temperature across the entire range of its distribution. Identical by design to panel a, panel b reveals a large and statistically significant decrease in birth rates from exposure to one >80°F day. Each 70°F–80°F day also reduces birth rates nine months later but to a lesser degree than >80°F (0.14 % vs. 0.40 %). Colder temperatures below the omitted 60°F–70°F category have little impact on birth rates nine months later. The confidence interval on <30°F implies that we can rule out an absolute effect size of 0.1 % or greater. The effect of <30°F in other exposure months is also minimal (see Online Resource Fig. S3). In sum, these estimates demonstrate that the temperature-fertility relationship has a "tipping point" (or kink) at a daily mean temperature of 70°F.

Using Different Functional Forms to Link Birth Rates and Temperature

We test the robustness of the results to using different functional form for the relationship between temperature and birth rates. Figure 3, panel a, models temperature using a spline function with knots at (degrees Fahrenheit) 10, 30, 40, 70, and 90. Panel b uses a model that relies on the fraction of the day in a given temperature bin, including a bin for the fraction of the day above 90°F. These models better capture the effects of temperatures above 90°F, something that our core model is less equipped to do given that daily *mean* temperatures seldom reach that threshold. In both panel a and panel b, the models reveal a tipping point at 70°F with respect to births nine months later. The negative effect at month 9 increases in magnitude as temperatures increase beyond 90°F. Importantly, the dynamic relationship shows a similar pattern to our core results: 90°F and higher temperatures displace some births from months 8–10 to months 11–13. Given that the results are qualitatively similar, we opt for using bins of daily mean temperature for both ease of exposition and consistency with previous studies (e.g., Barreca et al. 2016; Deschenes and Greenstone 2011).

A quadratic in monthly mean temperature, as used in earlier fertility studies, does not fit the data as well as the nonlinear temperature bins. Figure 4 illustrates this point by comparing the estimated effect of temperature on birth rates nine months later across three models with different temperature functional forms, with all other controls and number of lags/leads being identical. We show the results for our core model with 10°F bins of daily mean temperature; a spline of daily mean temperature with knots at (degrees Fahrenheit) 10, 30, 50, 70, and 90; and a quadratic function of the monthly mean temperature. The comparison across models is complicated by the fact that the marginal effect of a one-day change in temperature is conditional on the monthly mean temperature in the quadratic monthly model.[15] For simplicity, we assume that the temperature is identical for every day in the month.

The quadratic monthly model shows that a monthly mean shift in temperatures from 65°F to 85°F would result in a 7 % decline in births nine months later. Conversely, both our binned model and the spline model show that 30 additional days at 85°F would result in a 12 % decline in births. The quadratic model finds that colder temperatures cause higher birth rates, while the binned model and spline model indicate that temperatures below 60°F have no meaningful effect on birth rates. In other words, the quadratic representation of temperature, used in earlier work, understates the effect of high temperatures and overstates the effect of low temperatures from an inability to capture the tipping point near 70°F.

Robustness Checks

Online Resource 1 reports the results of various robustness checks. We show estimates using birth rates in levels and using the population of women aged 15–44 as the denominator in our birth rate measure (Fig. S4). Figure S5 reports estimates from two models: one without the state-year fixed effects and one without state-by-month quadratic time trends. As noted earlier, the state-by-year effects help address a potentially spurious correlation between declining fertility rates and increasing temperatures after the 1970s. We show in Fig. S6 (Online Resource 1) that high humidity levels have a modest impact on births rates. The estimated effects of hot temperatures are slightly diminished (relative to Fig. 2), suggesting that humidity is one natural mechanism through which temperature affects birth rates.

Table S2 (Online Resource 1) estimates a model that better captures the effects of *heat waves*, a span of three or five consecutive hot days. We find that marginal damage from one extra hot day is similar regardless of whether it occurred in isolation or as part of a heat wave. The estimates are similar across weekday and weekend, which suggests that we can rule out exposure at work or weekend behavior as the main mechanisms (Table S3, panel A). As a rough test of critical exposure period by time of day, we control for minimum and maximum temperature bins simultaneously in place of mean temperature bins (Table S3, panel B). We find that minimum temperature is a stronger predictor than maximum temperature, suggesting that the critical exposure period may be at nighttime. However, we cannot rule out the possibility that the estimates capture some other weather phenomenon, such as humidity or the temperature span itself, by simultaneously controlling for both minimum and maximum temperature.

[15]The marginal effect (dy) of a one-day change in the temperature (dt) in a quadratic model with monthly average temperature ($y = \beta_1 T + \beta_2 T^2$) is $dy / dt = \beta_1 dT / dt + 2\beta_2 T\, dT / dt$, where T is the average monthly temperature. Comparison with studies using average monthly temperature (Lam and Miron 1996; Seiver 1989) is also complicated by the fact their models were estimated separately for each state and race. For example, for whites in Georgia, LM's estimates imply that a one-day increase in temperature from 65°F to 85°F, in a month with mean temperatures of 65°F, would reduce birth rates nine months later by 0.17 %, which is less than one-half the magnitude of our estimate.

Explaining the Seasonality in Births

The estimates from our empirical model predict much of the seasonality in births in the United States. We apply our core model estimates (Fig. 2) to the observed distribution of temperatures over our sample period. Figure 5, panel a, illustrates the predicted values follow a nearly identical pattern, with births at a trough in April and a peak in August. The model underestimates birth rates in September and overestimates births in October through January, which may be partially explained by the December holidays causing a forward displacement in conceptions. That said, the model still explains nearly one-half of the variance (R^2 = .49) when we correlate the predicted points to the actual points in panel a. Note that a substantial portion of the goodness of fit comes from accounting for the rebound in births. Specifically, when we include only months 9 and 10 in our model, similar to past research, the R^2 for the predicted-actual comparison falls to 0.23. Panel b (Fig. 5) shows that the model also predicts substantially more seasonal variability in the South relative to other regions of the United States, consistent with the actual seasonality across regions (Fig. 1).

Exploring the Role of Adaptation

Next, we restrict the model to exposure months 8–13 to improve statistical power and facilitate exposition of the results. All other controls are identical to our core model (Eq. (1)). We focus on the effects of days above 80°F, although our model controls for other temperature bins. Table 2, panel A, illustrates that the main estimates on >80°F days in months 8–13 are unchanged using the narrower set of exposure months. In the following discussion, we explore how the effect of >80°F days vary by climate and period.

Heterogeneity by Climate

To investigate the role of adaptation in response to long-term average temperatures, we split our sample of states in half based on each state's average exposure to days above 80°F. Table 2, panel B, shows that the magnitude of the effects in months 8–10 is smaller in states with warmer climates. The difference between "cold" and "hot" states at month 9 is important: one >80°F day causes a 0.37 % decrease in births in hot states versus a 0.55 % decline in cold states, corresponding to a 43 % relative difference in the magnitude of the coefficients (statistically significant). These results suggest that long-term adaptation, as embodied by differential historical exposure to high temperature days, plays a role in mitigating the effects of high temperatures. However, we cannot rule out the possibility that another unobserved factor, such as wealth, accounts for some of the heterogeneity across hot and cold states. Thus, we view these cross-climate comparisons as suggestive and worthy of future research.

Heterogeneity Over Time

Figure 6 further investigates the changes over time by documenting the temperature-fertility relationship by decade. Here, we interact each temperature bin with an indicator for each decade. We present only the marginal effects of each additional >80°F day on log birth rates nine months later, although we include the full set of temperature bins across exposure months 8–13. In the 1940s, 1950s, and 1960s, exposure to one additional >80°F day consistently causes a 0.6 % reduction in the birth rate nine months later. The effect size monotonically decreases after the 1960s. By the 2000s, one additional >80°F day causes the birth rate nine months later to decline by only 0.2 %. The effect size is relatively smaller in the 1930s than in the 1940s, 1950s, or 1960s, possibly because of random measurement error in temperature assignment given that the birth data are reported by state of occurrence in the 1930s. This dampening of the temperature-fertility relationship since 1950 follows the patterns of residential air conditioning diffusion over the same period, which we investigate in the following section.

The Role of Air Conditioning

We explore whether residential air conditioning (AC) can explain the decline in the temperature-fertility relationship since 1950 using the approach of Barreca et al. (2016). We restrict our sample to the 1950–2010 period to avoid any potential confounders related to the Great Depression and World War II. Our measure of AC coverage by state of residence is linearly interpolated between the 1960, 1970, and 1980 decennial censuses and is assumed to be 0 in 1950.[16] We use the growth rate in AC coverage between 1970 and 1980 to project out to 2010, while capping the coverage at 100 %.[17] Our work builds on that of Seiver (1989), who correlated changes in AC coverage between 1960 and 1980 with changes in birth seasonality. We extend Seiver's work by relating changes in the temperature-fertility response function explicitly, allowing us to include state-by-month time trends to mitigate possibly spurious correlation between trends in birth seasonality across states and AC adoption.

We take a few steps to account for the possibility that the adoption of AC is correlated with time-varying omitted factors that may also affect birth rates, such as changes in wealth. First, and already present in our core model, we control for state-year fixed effects to account for those factors that correlate with our state-year AC measure but are independent of month of year. Second, we control for the interaction between the temperature variables and a linear time trend to mitigate concerns that the increase in AC coverage correlates with secular trends in vulnerability to temperature extremes. Third, we add temperature interactions with state-year measures for a number of possible confounders: the fraction of women with 12 or more years of schooling, access to legal abortion, unmarried women's legal access to oral contraceptives before age 21, access to electricity, log per capita income, and fraction of workers with high risk of exposure to ambient temperatures, such as those working agriculture (Bailey 2006; Goldin 2006; Goldin and Katz 2002; Guldi 2008; Haines 2004; Levine et al. 1996; Ruggles et al. 2010).

We find that the diffusion of residential AC correlates significantly with changes in the temperature-fertility relationship, especially for high temperatures. Table 3, panel A, presents the AC interaction terms on the >80°F variables for the full set of months 8–13 (reported in 1/100 log points).[18] Positive and statistically significant AC coefficients at months 8, 9, or 10 would imply that AC mitigates temperature's influence around the time of

[16]We define "air conditioning" as at least one air conditioning unit or central air conditioning.
[17]Fig. S7 (Online Resource 1) illustrates the estimated AC coverage by region. See Biddle (2008) for a discussion on the historical determinants of AC in the United States. Assuming classical measurement error, we expect the estimates to be biased downward. Additionally, clustering the standard errors at the state level helps mitigate concerns about the interpolation generating serially correlated errors.

conception. Indeed, the interaction term is positive and statistically significant at months 9 and 10. The magnitude is large: an 80 percentage point increase in AC coverage, which corresponds to the uptake over this period, reduces the impact at month 9 by a meaningful 0.15 percentage points in absolute terms (0.8 ×0.00192). We do not observe a statistically significant dampening of the rebound in months 11, 12, and 13, although we cannot rule out meaningful effect sizes.

Next, panel B of Table 3 adds controls for other interactions with factors that may have contributed to historical changes in the effects of high temperature on birth rates. After we account for these additional factors in panel B, the coefficient on the AC interaction at month 9 is still statistically significant and nearly identical in magnitude. Nonetheless, we cannot definitively rule out the possibility that changes in AC coverage are endogenous to changes in the temperature-fertility relationship over time.

Investigating the Critical Week of Exposure

Impacts on Conception-Survival Rates (1969–2003)

As noted earlier, hot days cause a relatively large reduction in births 10 months later, suggesting that the critical exposure period occurs just before conception. To more precisely test this hypothesis, we exploit the fact that detailed natality data (1969–2004) report the date of last menses, which can be used to infer the date of conception. We assume that conception occurs two weeks after the start of the last menses.[19] For this analysis, the unit of observation is at the state and year-week of conception. Given that we observe only those conceptions that survive to birth, our analysis cannot distinguish between fetal losses and decreases in conceptions.[20] As such, we define the *conception-survival rates* as the estimated number of conceptions that survive to birth in a given state-year-week per 1,000 population.[21] We exclude 1968 and 2004 conception years from our sample because some births will be realized outside the years when data are available. We also drop states where the date of last menses is not reported for one or more years.[22]

We estimate the following model:

$$Y_{st} = \sum_{j}^{J} \sum_{k}^{K} \beta_k^j \mathbf{TEMP}_{s,t-k}^j + \sum_{k}^{K} \gamma_k \mathbf{X}_{s,t-k} + \alpha_{sw} + \delta_t + \theta_{sy} + e_{st}, \qquad (2)$$

where Y is the log of the conception-survival rate in state s in year-week t. **TEMP** is the main vector of temperature bins, and **X** is a vector of precipitation controls in state s in year-

[18] The interaction between temperature and AC is small and statistically insignificant at colder temperatures, further supporting the presumed temperature control mechanism provided by AC.

[19] Fehring et al. (2006:376) surveyed 141 women between 3 to 13 cycles each and found that “95 % of the cycles had all 6 days of fertile phase between days 4 and 23, but only 25 % of participants had all days of the fertile phase between days 10 and 17.”

[20] In a review article, Boklage (1990) found that close to three-quarters of conceptions do not survive past six weeks of gestation. Wilde et al. (2017) provided evidence that temperature improved long-term outcomes for surviving cohorts most likely by selectively culling weaker fetuses. See Catalano et al. (2006), Sanders and Stoecker (2015), and Trivers and Willard (1973) for more detail on the role that the fetus gender plays in survival to birth.

[21] We divide each calendar into 52 “weeks,” where the 365th day and 366th day (during leap years) are included in the 52nd week. State population data come from the National Cancer Institute (2013) and are assigned at the state-year level.

[22] This restriction excludes Alabama, Arkansas, Connecticut, Delaware, Florida, Georgia, Idaho, Maine, New Mexico, Oregon, Pennsylvania, Texas, Virginia, and Wisconsin.

week $t-k$. We also control for state-by-week fixed effects (α_{sw}), year-by-week dummy variables (δ_t), and state-by-year fixed effects (θ_{sy}) to help isolate exogenous changes in temperature.[23] We allow temperature effects for up to 19 weeks before and 6 weeks after the time of conception (i.e., $k = -19, -18, \ldots 6$) to identify the critical exposure period.[24] The 19 lag weeks allow for the possibility that conceptions could shift to later cycles. The 6 forward weeks address the possibility that temperature shocks after conception and early on in the pregnancy might cause fetal losses.

The estimates in Fig. 7 illustrate the effect of one >80°F day on the log conception-survival rate by weeks from the estimated week of conception. Additional >80°F days have no discernable effect on the conception-survival rate in the week of conception (i.e., week 0). Instead, temperature has a two-week delayed impact on the chances that a conception survives to birth. One >80°F day two weeks prior to the estimated week of conception reduces the conception-survival rate by a statistically significant 0.6 %. Panel b drops data for menses reported on day 1, 5, 10, 15, 20, 25, 28, or 30 of the month when there is heaping, possibly because of measurement error. The estimates in panel b are qualitatively similar.

These estimates suggest that we can rule out high temperature causing an *immediate reduction* in sexual activity. If temperature affected sexual activity, we would most likely observe a change in the conception-survival rate in the contemporaneous week, provided that there was no countervailing impact on reproductive health or change in birth control use. However, we find that the chance of conception is determined by the temperature two weeks prior to conception, which is unlikely to be due to some latent effect on sexual behavior. The most likely explanation is that temperature harms reproductive health two weeks prior to the time of conception in some latent or persistent way. Indeed, experimental studies on mammals have provided plausible evidence that high temperatures have a delayed effect on spermatogenesis (Hansen 2009). Bulls exposed to temperatures between 88°F and 95°F (relative to a control group at 73°F) had diminished spermatogenesis from two to eight weeks later (Meyerhoeffer et al. 1985). Female exposure to high temperatures may also affect the menstrual cycle and thereby affect conception, although experimental studies have suggested that this channel may be muted (Hansen 2009). Future research into the biological mechanisms is warranted.

Conclusion

We examine the relationship between ambient temperature and birth rate dynamics in the United States over nearly a century. We find that unusually hot days cause a large fall in birth rates approximately 8 to 10 months later and provide novel evidence that this is followed by a partial rebound in birth rates at 11, 12, and 13 months. Although the observed rebound may offset some of the impacts on completed fertility, evidence from other studies suggests that a shift toward summer births (in itself) could have both short- and long-term social costs (Currie and Schwandt 2013). In the short term, infant health is worse because of

[23]We partial out the state-by-week fixed effects prior to estimation to reduce the computational burden.
[24]Unlike with Eq. (1), temperature shocks could affect conception rates after the fact; that is, there is no placebo check in Eq. (2).

increased exposure to hot weather in the third trimester (Deschenes et al. 2009). As with other early-life health shocks (Almond and Currie 2011), recent evidence suggests potential long-term consequences to this increased *in utero* exposure to high temperatures (Isen et al. 2017; Wilde et al. 2017).

We also find evidence that high temperatures reduce fertility through worse reproductive health rather than diminished sexual activity. The reduction in reproductive health has important distributional effects depending on the individual's (or couple's) preferences and stage of reproductive life. For individuals who do not desire a child, a reduction in conception chances might be beneficial. Individuals who do desire a child but are nearing the end of their reproductive life will incur higher costs from a delayed conception. Because maternal age at first birth has been increasing, these temperature disruptions are likely to be more costly over time (Mathews and Hamilton 2016).

Echoing a recent study on mortality (Barreca et al. 2016), providing low-cost access to AC may be an effective tool for mitigating the fertility costs of hot weather. We document a large reduction in the temperature-fertility relationship over our 80-year sample period and find that AC can explain one-third of the dampening of this relationship over time. However, the costs of increased AC usage include greenhouse gas emissions, underscoring the fundamental dilemma in using energy-intensive technologies to adapt to climate change.

Finally, our results shed new light on the debate regarding the key determinants of birth seasonality. Temperature around the *time of conception* is likely the single-most important determinant of birth seasonality in the United States because it both immediately reduces conception chances and causes some of the susceptible population to conceive in later months. Beyond this, a portion of the seasonality could still be a function of individual preferences about expected temperature around the *time of birth* (Buckles and Hungerman 2013), something that we cannot address with our quasi-experimental approach. Other environmental factors, such as sunlight, may also have an influence on birth seasonality and are worthwhile of exploration. More research is needed to assess how temperature might influence birth seasonality in other parts of the world with particular attention to high-poverty areas that have limited access to adaptive technology, such as AC.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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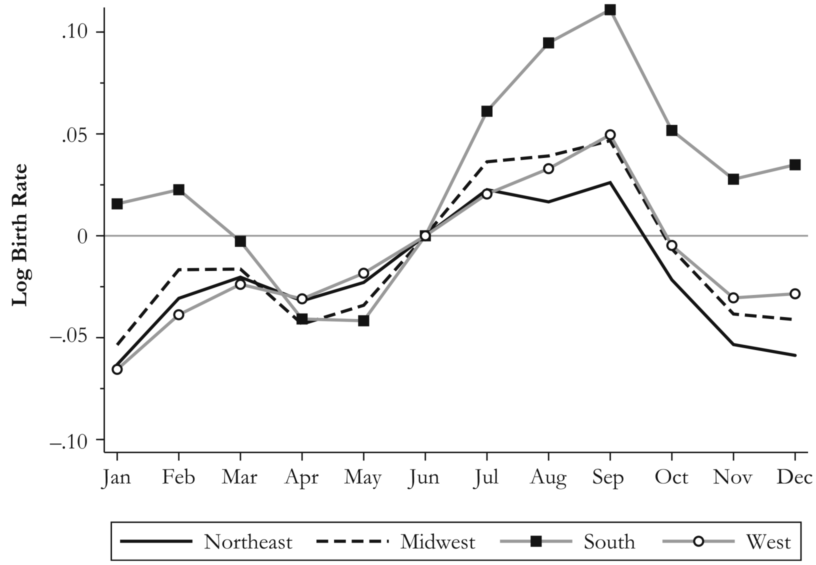

Fig. 1.

Seasonality in daily birth rate per 100,000 residents, 1931–2010, by census region. Calculations use state-year populations as weights

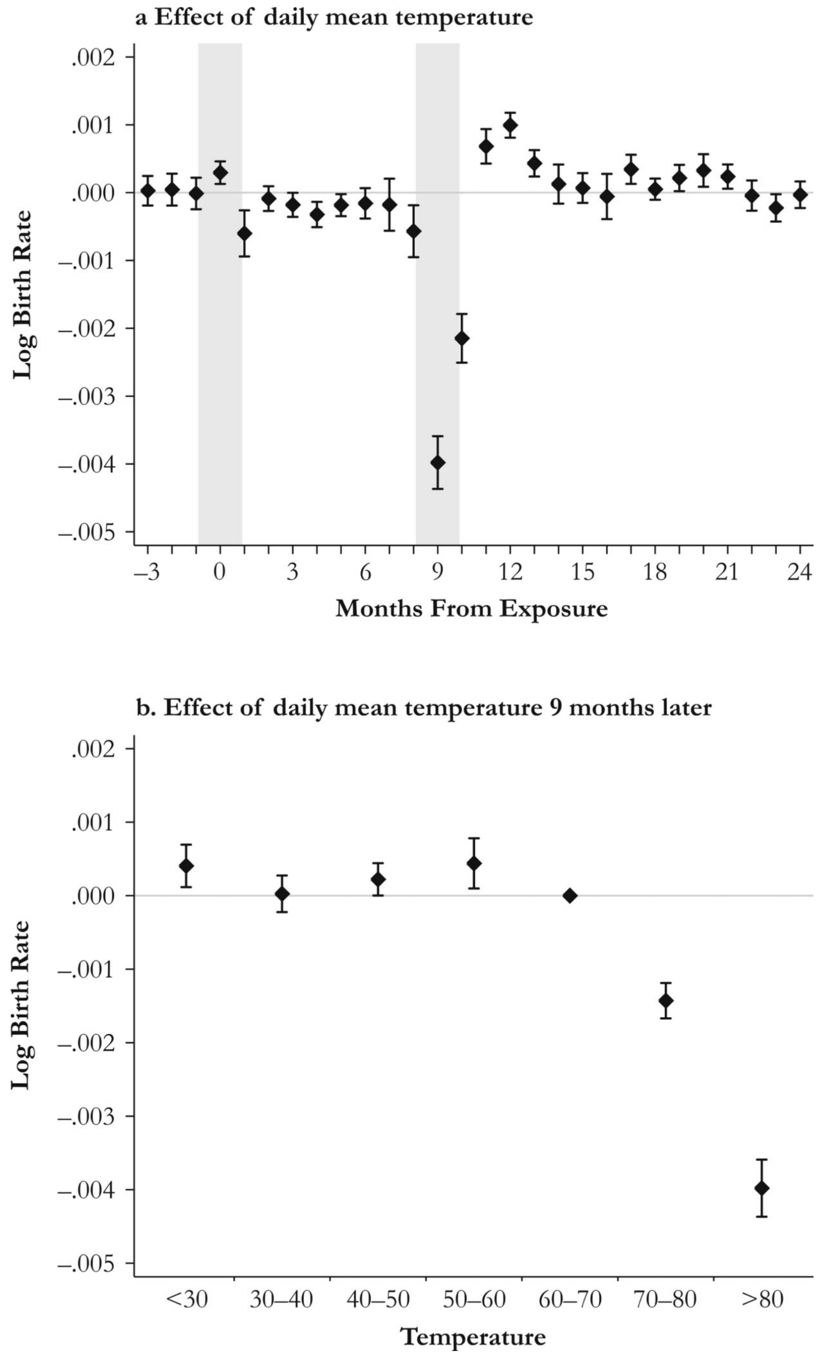

Fig. 2.

Estimated temperature-fertility relationship: Effect of daily mean temperature on log birth rate. The diamonds are the point estimates, and the brackets represent +/− 2 standard errors. The estimates can be interpreted as the impact on the log monthly birth rate, in log points, of one additional day with a mean temperature >80°F relative to 60°F to 70°F. The model has year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar month quadratic time trends, and state-year fixed effects. We control for fraction of days with precipitation between 0.01 and 0.50 inches and more than 0.51 inches in each month. In addition, we control for effects for up to 24 months after exposure (and 3 months prior to exposure as a placebo check). The regressions are weighted by state-year population in the preceding year. Standard errors are clustered at the state level. The gray shading highlights both 0 and 9 months from exposure

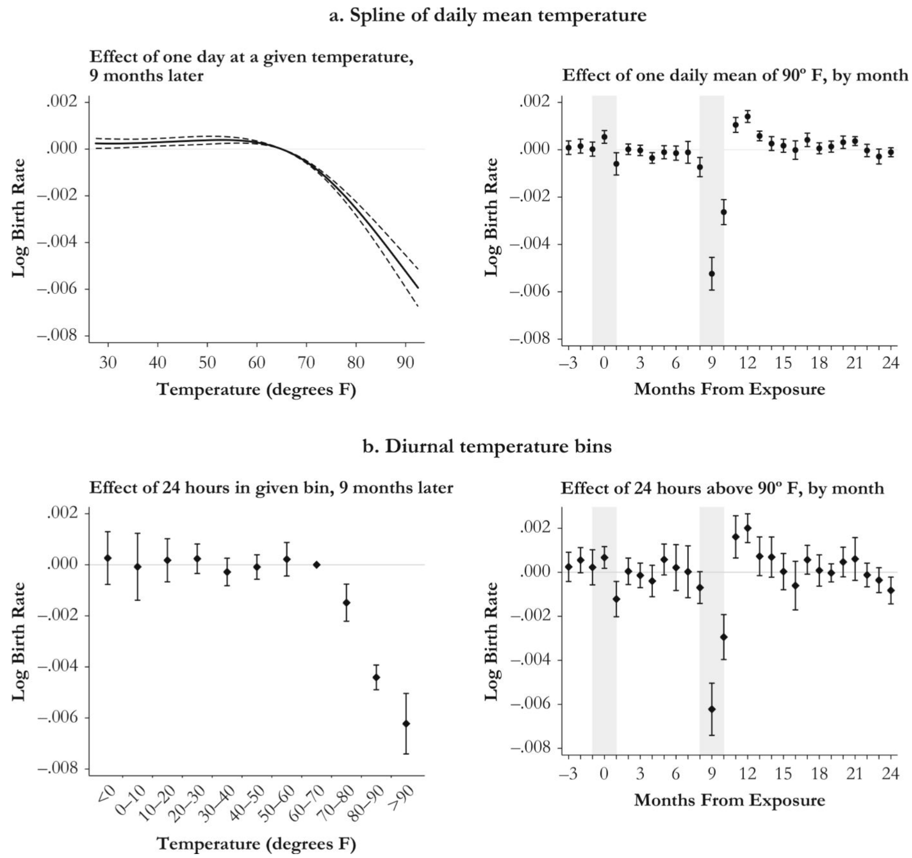

Fig. 3.

Estimated temperature-fertility relationship: Different functional forms for temperature. In the spline model, the estimates come from a cubic polynomial spline function with knots at daily mean temperatures (in degrees Fahrenheit) of 10, 30, 40, 70, and 90. The diurnal model captures the proportion of the day in a given 10°F interval, where diurnal temperatures are linearly interpolated from the daily maximum and daily minimum temperature. The bounds for the diurnal model are set at 0°F and 90°F. Each model has identical controls to our core model and the same number of lags and leads

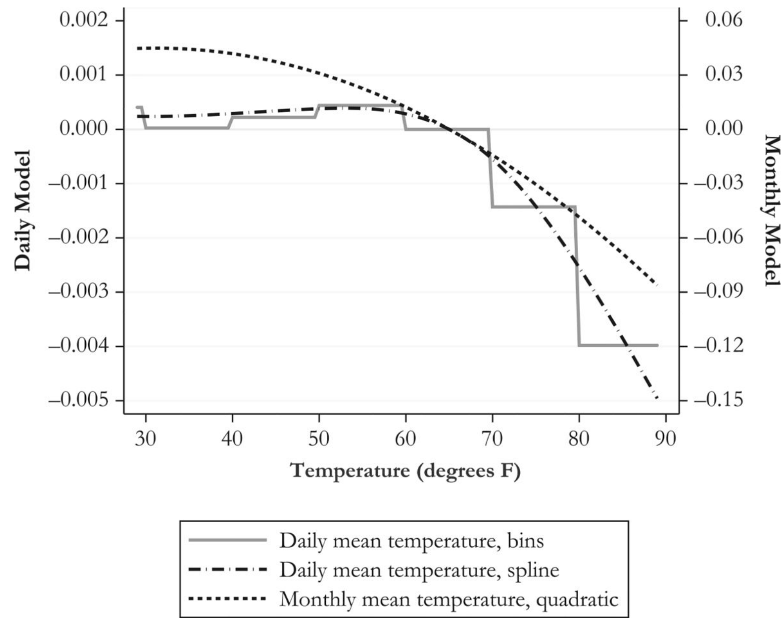

Fig. 4.

Estimated temperature-fertility relationship: Comparison with monthly quadratic model. The daily bins model refers to our core model. See notes to Fig. 2 for details on that model. The spline estimates come from a cubic polynomial spline function with knots at daily mean temperatures (in degrees Fahrenheit) of 10, 30, 40, 70, and 90. The monthly quadratic model has identical controls to our core model and the same number of lags and leads, except that temperature is a quadratic function of the monthly mean temperature

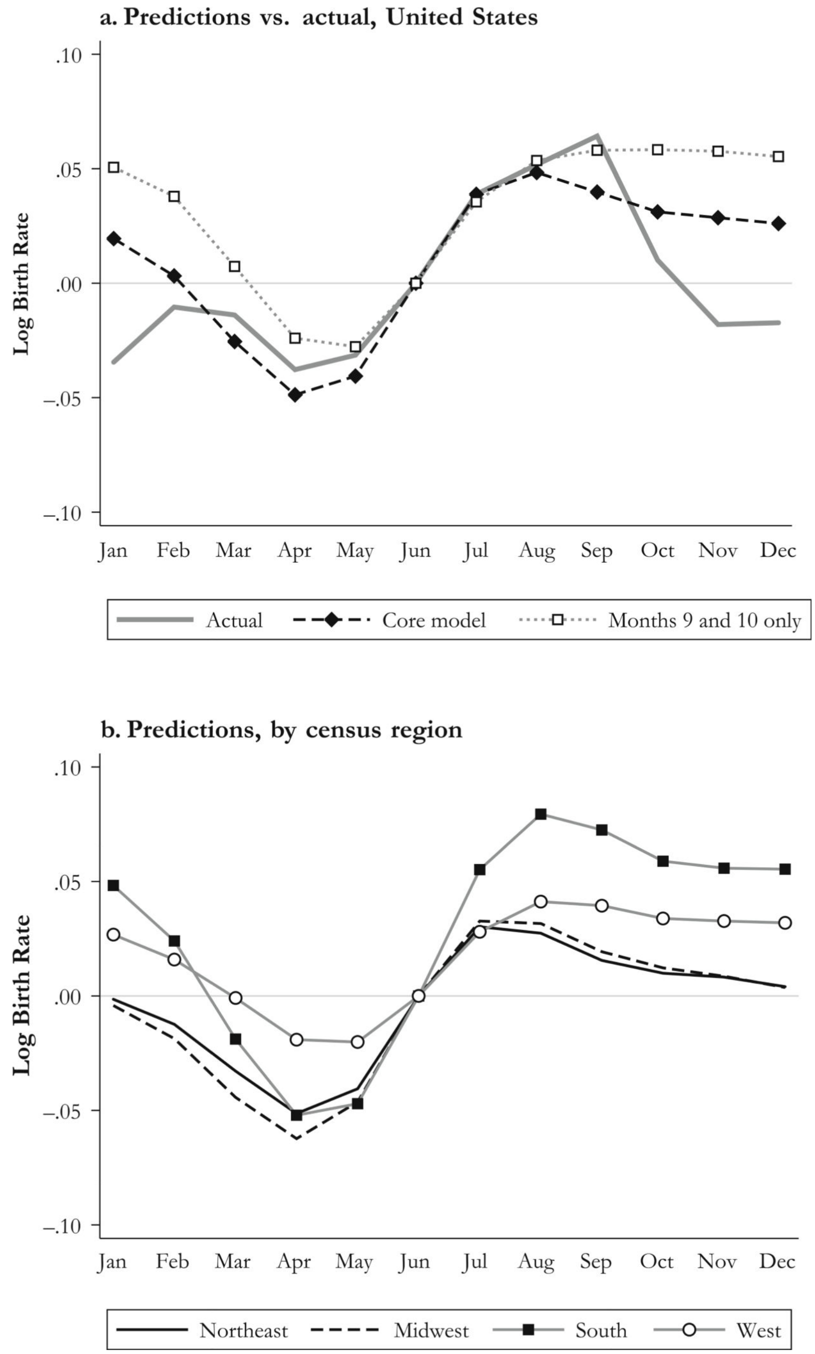

Fig. 5.

Model predictions of log birth rate. See notes to Fig. 2 for details on the core model, which controls for the full set of exposure months (−3, −2, …, +24). In Panel a, the "Months 9 and 10 only" model controls only for exposure in months 9 and 10. We use only the temperature estimates to make these predictions and ignore rainfall and all other controls. We recenter both the observed and predicted values around June, so the values should be interpreted as deviations, in log points, from June

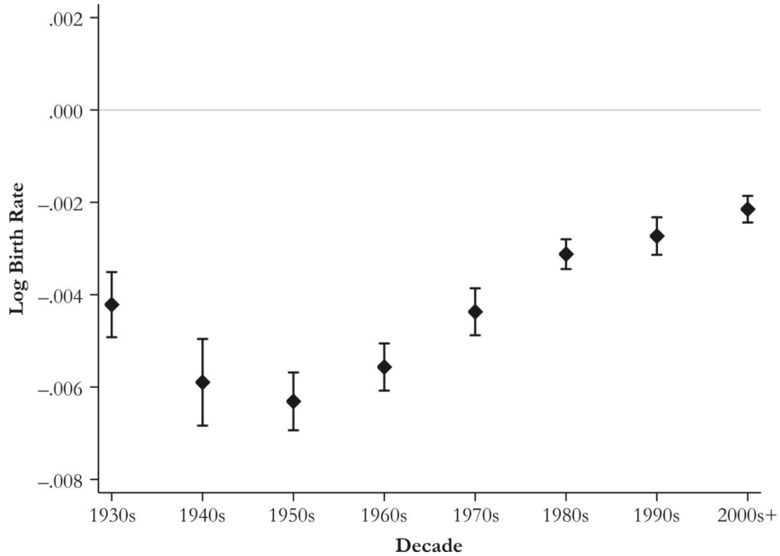

Fig. 6.
Estimated temperature-fertility relationship: Effect of daily mean temperature >80°F relative to 60°F to 70°F on log birth rate 9 months later, by decade. The diamonds are the point estimates, and the brackets represent +/− 2 standard errors. The model controls for exposure months 8–13. We use the full sample of years and interact the temperature variables with an indicator for the given decade. We include 2010 in the 2000s. See notes for Fig. 2 for details on the other model controls

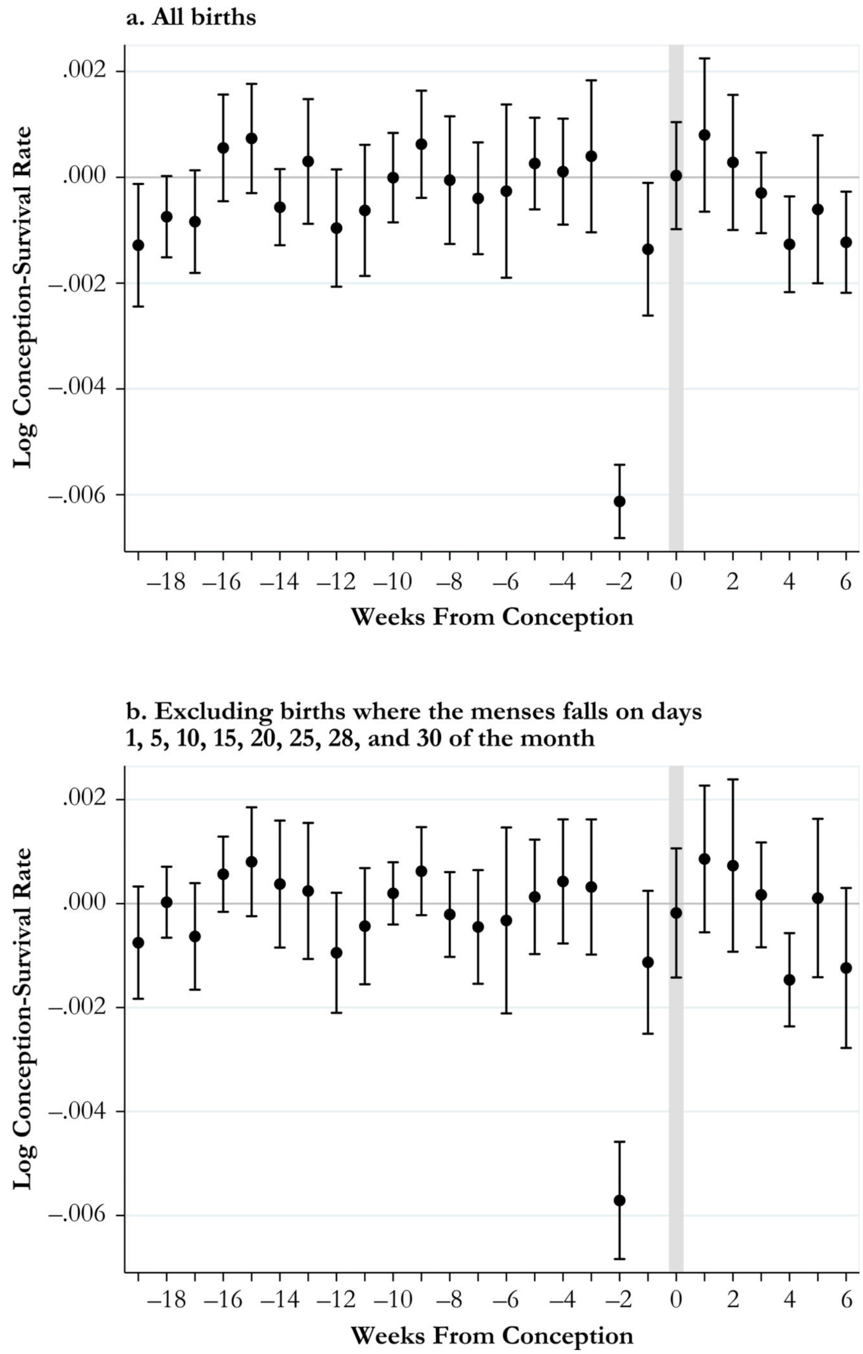

Fig. 7.

Estimated impact around the time of conception: Effect of daily mean temperature >80°F relative to 60°F to 70°F on log conception-survival rate. The coefficient can be interpreted as the effect of one >80°F day some weeks from the estimated week of conception on the log of the number of conceptions that survive to birth in week 0. The gray shading highlights the approximated week of conception. The natality data have date of last menses beginning in 1969, which we use to infer week of conception. We assume that the week of conception is two weeks after the reported date of last menses. We calculate the conception-survival rate as the total number of conceptions in a given week divided by the state-year population in 1,000s. States that do not report last date of menses in any one year are dropped entirely from the sample; these excluded states are AL, AR, CT, DE, FL, GA, ID, MA, NM, OR, PA, TX, VA, and WI. We partial out state-by-week fixed from the outcome and predictor variables prior to estimation to reduce the computational burden. The model then includes year-month-week fixed effects and state-by-year fixed effects. The regressions are weighted by state-year population in the preceding year. Standard errors are clustered at the state level

Table 1

Summary statistics on daily birth rates and daily weather, 1931–2010

Sample	All States	Northeast	Midwest	South	West
Daily Births per 100,000 Residents	4.7	4.3	4.7	4.9	4.9
Mean Temp <;30°F	2.9	4.2	5.3	0.8	1.3
Mean Temp 30°F to 40°F	3.4	4.9	4.6	2.2	2.1
Mean Temp 40°F to 50°F	4.4	5.1	4.3	3.9	4.5
Mean Temp 50°F to 60°F	5.6	5.2	4.7	5.1	8.5
Mean Temp 60 °F to 70°F	6.1	5.7	5.5	5.9	8.2
Mean Temp 70°F to 80°F	5.8	4.7	5.1	7.9	4.2
Mean Temp >80° F	2.3	0.6	1.0	4.7	1.5
No Precipitation	21.4	19.7	20.8	21.6	24.3
Precipitation = 0.00-0.50 Inches	7.0	8.3	7.8	6.4	5.1
Precipitation = 0.50+ Inches	2.1	2.4	1.9	2.5	1.0
Number of State-Months	47,004	8,640	11,508	16,296	10,560
Number of States	49	9	12	17	11

Notes: For temperature and precipitation, the data represent average number of days per month. Calculations use state-year populations as weights. The births are by state of residence for the years 1942 onward, and state of occurrence in the 1931–1941 period. South Dakota does not enter the sample until 1932, and Texas does not enter until 1933. Alaska and Hawaii are excluded from the sample.Washington, DC, is treated as a state in our analyses.

Table 2

Heterogeneity in the effect of daily mean temperature >80°F relative to 60°F to 70°F on log birth rate (× 100), by months from exposure

	Months After Temperature Shock						Cumulative
	8	**9**	**10**	**11**	**12**	**13**	**8-13**
A. All States and Years							
1931–2010	−0.055	−0.396	−0.209	0.066	0.098	0.049	−0.446
	(0.015)*	(0.016)*	(0.014)*	(0.009)*	(0.012)*	(0.007)*	(0.034)*
B. By Climate							
Hot states	−0.050	−0.368	−0.189	0.061	0.098	0.046	−0.401
	(0.017)*	(0.017)*	(0.016)*	(0.011)*	(0.013)*	(0.009)*	(0.033)*
Cold states	−0.103	−0.536	−0.311	0.091	0.104	0.053	−0.702
	(0.018)*	(0.028)*	(0.024)*	(0.021)*	(0.018)*	(0.017)*	(0.065)*
Difference	0.052	0.168	0.122	−0.030	−0.006	−0.006	0.301
	(0.021)*	(0.035)*	(0.031)*	(0.026)	(0.018)	(0.019)	(0.070)*

Notes: The estimates can be interpreted as the impact on the log monthly birth rate (×100) of one additional day with a mean temperature >80 °F relative to 60 °F to 70 °F. The model controls for exposure months 8–13. We control for fraction of days with precipitation between 0.01 and 0.50 inches and more than 0.51 inches in each month as well as the effects in other temperature bins (i.e., in degrees Fahrenheit, <30, 30–40, 40–50, 50–60, and 70–80) in each month. The controls include year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar-month quadratic time trends, and state-year fixed effects. The regressions are weighted by state-year population in the preceding year. Standard errors, clustered at the state level, are shown in parentheses. Here, we interact the temperature variables with an indicator for whether the state is a "hot state" (panel B), which indicates states that have more than the median number of >80 °F days over the sample period.

* $p < .05$

Table 3

Impact of residential air conditioning (AC) on the temperature-fertility relationship: Interaction effect with daily mean temperature >80°F relative to 60°F to 70°F on log birth rate (× 100), by months from exposure

	Months After Temperature Shock						**Cumulative**
	8	**9**	**10**	**11**	**12**	**13**	**8-13**
A. Only AC- Temperature Interactions							
Days >80°F	−0.123	−0.712	−0.349	0.125	0.154	0.070	−0.835
	(0.018)*	(0.033)*	(0.033)*	(0.024)*	(0.024)*	(0.022)*	(0.077)*
AC × >80 °F	−0.055	0.192	0.114	−0.029	−0.065	−0.038	0.121
	(0.076)	(0.052)*	(0.048)*	(0.053)	(0.045)	(0.054)	(0.119)
B. With Other Interactions							
Days >80°F	−0.400	−0.707	−0.215	−1.203	0.056	−0.781	−3.249
	(0.670)	(0.621)	(0.607)	(0.615)	(0.474)	(0.405)	(1.610)*
AC × >80 °F	0.005	0.225	0.073	0.009	−0.121	−0.011	0.180
	(0.058)	(0.069)*	(0.049)	(0.058)	(0.047)*	(0.051)	(0.149)
Abortion × >80°F	0.018	0.058	0.009	−0.027	−0.012	−0.021	0.025
	(0.041)	(0.043)	(0.037)	(0.045)	(0.029)	(0.032)	(0.059)
Pill 21+ × >80°F	−0.040	0.010	0.024	−0.007	−0.001	0.044	0.029
	(0.031)	(0.041)	(0.022)	(0.035)	(0.038)	(0.028)	(0.081)
High school diploma × >80°F	−0.141	−0.126	0.288	0.063	0.121	−0.080	0.125
	(0.236)	(0.204)	(0.207)	(0.183)	(0.132)	(0.136)	(0.609)
High-risk work × >80° F	−0.052	−0.215	−0.502	0.758	−0.584	0.113	−0.482
	(0.646)	(0.515)	(0.402)	(0.252)*	(0.301)	(0.295)	(1.335)
Electrification × >80°F	0.130	−0.401	0.036	−0.524	0.460	−0.475	−0.775
	(0.451)	(0.414)	(0.337)	(0.381)	(0.271)	(0.188)*	(1.008)
Log income × >80° F	0.025	0.051	−0.021	0.171	−0.028	0.139	0.338
	(0.062)	(0.070)	(0.066)	(0.056)*	(0.056)	(0.049)*	(0.145)*

Notes: See notes for Fig. 2 for a description of the basic model. Standard errors, clustered at the state level, are shown in parentheses. The table presents estimates from Eq. (1), with the temperature bins as main effects but with the temperature variables interacted with the added variables, such as air conditioning (panel A). The regressions are weighted by state-year population in the preceding year. The sample period is 1931–2010. See the text for a description of the air conditioning variable. We have state-level information on female education levels from decennial censuses between 1930 and 2000 and from the annual American Community Surveys between 2001 and 2010.We linearly interpolate the missing data between the decennial censuses.We focus on females aged 18–45 with a high school diploma. We create an indicator equal to 1 if abortion was legal in a state in that year. As with prior literature (Levine et al. 1996), we assume that early repeal states (California, Washington, and New York) legalized abortion in 1970 and that all other states legalized it in 1973. The "Pill 21+" variable controls for whether unmarried women under the age of 21 could legally obtain oral contraceptives, using data from Bailey (2006). *High-risk work* is defined as the fraction employed in agriculture, forestry, fisheries, mining, manufacturing, transportation, and utilities, following Graff Zivin and Neidell (2014); the data come from the decennial census and are interpolated between decades. Electrification data come from Barreca et al. (2016). Income data come from the Bureau of Economic Analysis. We assign treatment based on the values of the added variables in the year prior to the year of birth.

* $p < .05$