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

Alan Barreca, Tulane University, IZA, and NBER*
Olivier Deschenes, UC Santa Barbara, IZA, and NBER
Melanie Guldi, University of Central Florida

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Barreca (corresponding author) can be contacted via email at abarreca@tulane.edu, Deschenes at olivier@econ.ucsb.edu, and Guldi at mguldi@ucf.edu.

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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 above 80 °F cause a large decline in birth rates 8 to 10 months later. 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. We present novel evidence that hot weather harms fertility via reproductive health as opposed to sexual activity. Historical evidence suggests air conditioning could be used to substantially offset the fertility costs of high temperatures.

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Alan Barreca
Department of Economics
206 Tilton Hall
Tulane University
New Orleans, LA 70118
IZA, and NBER
email: abarreca@tulane.edu

Olivier Deschenes
Department of Economics
2127 North Hall
University of California
Santa Barbara, CA 93101-9120
IZA, and NBER
email: olivier@econ.ucsb.edu

Melanie Guldi
Department of Economics
College of Business Administration
University of Central Florida
4336 Scorpius Street
Orlando, FL 32816-1400
email: mguldi@ucf.edu

I. Introduction

> All that we can do, is to keep steadily in mind that each organic being is striving to increase at a geometrical ratio; that each at some period of its life, during some season of the year, during each generation or at intervals, has to struggle for life, and to suffer great destruction.
>
> — Charles Darwin, *On The Origin of Species (1859)*

Despite considerable economic advances since Charles Darwin's time, weather still seems to play an important role in human health and welfare. Recent research demonstrates that ambient temperature affects a variety of socioeconomic outcomes, including mortality, labor supply, and income.[1] Fertility is one area where the costs of weather shocks are less clear, though the strong seasonality in births across many countries suggests temperature may play an important role. The most convincing temperature-fertility study to date is Lam and Miron (1996), which 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 can adapt to mitigate immediate fertility costs, namely by shifting conceptions to later months. Second, we investigate whether reproductive health at conception or sexual activity is the causal mechanism underlying the relationship.[2] More broadly, our research quantifies the fertility costs of temperature shocks, which are likely to increase in frequency with unabated climate change. The fact that many developed countries suffer from "below replacement" fertility rates underscores the pressing need for this research.[3]

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*

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[1] For mortality, see Deschenes and Moretti (2009), Deschenes and Greenstone (2011), Barreca (2012), and Barreca et al. (2016). For infant health, see Deschenes et al. (2009). For income, see Deryugina and Hsiang (2014). For labor supply, see Graff Zivin and Neidell (2014). Dell et al. (2014) summarizes this literature.

[2] Experimental research on animal mammals (Hansen, 2009) suggest that high temperatures might adversely affect fertility via impacts on spermatogenesis.

[3] In many developed countries, total completed fertility rates are currently below 2.1, which is the rate at which the population "replaces" itself (absent migration). In 2010, total completed fertility rate is estimated at 1.9 in the United States and only 1.7 in high-income countries (World Bank, 2013). These below-replacement rates are a concern for funding of pay-as-you-go pensions, like Social Security (Goss, 2010).

temperatures so as to avoid seasonal confounders, like 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 non-linear effects at the temperature extremes, which is especially important for assessing the potential risks of climate change.

Our estimates indicate that hot weather causes a significant decline in birth rates 8 to 10 months later. One additional "hot day" above 80 °F, relative to one day between 60 and 70 °F, causes a 0.4% decrease in birth rates 9 months later.[4] After the initial decline, birth rates partially rebound over the next few months; the increase in births in months 11, 12, and 13 offsets about 32% of the decline in births in months 8, 9, and 10. We also see a small rebound about one year after the initial decline, suggestive that some of the affected population has preferences for sexual activity and/or conceiving in certain calendar months. Cold temperatures, such as days below 30 °F, have relatively little impact on birth rates.

To illustrate the potential for long-term adaptation, we show that states that are more accustomed to higher temperatures are less vulnerable to random fluctuations in hot days. Also, we 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. Other historical factors, including access to birth control and changes in outdoor employment have little effect on the temperature-fertility relationship.

We provide two novel pieces of evidence regarding the mechanisms underlying the initial decline in fertility. First, using the American Time Use Survey, we find that higher temperatures actually *increase* the same-day probability unmarried individuals engage in "personal or private activities", which includes sexual activity; for married individuals we fail to detect such an effect. Second, we use detailed Natality data, with information on the mothers' last normal menses, to more precisely estimate the effects of temperature around the time of conception. We find that higher temperatures do not have an immediate impact on conception chances. Instead, higher temperatures reduce the number of conceptions that survive to birth when exposure occurs two weeks prior to the date of conception. These two findings suggest that the initial decline in births is due to worse reproductive health as opposed to diminished sexual activity.

[4] This measured effect on fertility is notably larger than the corresponding effect of >80 °F temperatures on mortality. For example, Barreca et al. (2016) find that an additional day above 80 °F, relative to one day between 60 and 70 °F, increases mortality rates by less than 0.2%.

Our work indicates that policy makers and scientists should consider reproductive health as an important and underexplored cost of climate change.[5] Increasing temperatures due to climate change are likely to raise the cost of conceiving during summer months. While the short-term shift in conceptions to the fall and winter helps mitigate impact on long-term birth rates, this shift will have an added health cost: more births will occur in the summer when infants are exposed to considerably higher temperatures during the third trimester and neonatal period. In addition to increased short-term costs, like hospitalization, increased exposure to hot weather during critical periods of early life could also have lasting impacts on human capital accumulation.[6]

II. Conceptual framework of the dynamic temperature-fertility relationship

For a non-pregnant female, the chance of conceiving in any given (reproductive) cycle, henceforth referred to as "conception probability", is a function of her and her male partner's reproductive health and their coital frequency. The best evidence supporting a link between temperature and reproductive health comes from experiments on mammals. Spermatogenesis appears to be particularly sensitive to higher temperatures (Hansen, 2009). Paul et al. (2008) showed that *in vitro* fertilization was less successful when using sperm from male mice exposed to temperatures of 108 ºF. Bulls that were exposed to temperatures between 88 and 95 ºF had diminished spermatogenesis from two to eight weeks later (Meyerhoeffer et al., 1985). Conversely, *female* exposure to high temperatures may have only a minimal effect on fertilization (Hansen, 2009). However, experiments on female cattle and mice showed that exposure to higher temperatures both before ovulation and after insemination hindered the development of fertilized oocytes (Putney et al., 1988; Putney et al., 1989).

With regards to humans, evidence of a link between temperature and reproductive health comes mostly from seasonal relationships. Prior work has found that spermatogenesis, testosterone levels, menstruation, ovulation, and implantation are worse during the summer

[5] In the 2014 International Panel on Climate Change Synthesis Report (IPCC 2014), there was no mention of fertility costs. Conversely, human mortality is mentioned multiple times.
[6] Almond and Currie (2011) survey the fetal-origins literature, which provides compelling evidence that early-life health shocks have consequences for lifelong outcomes. However, the causal relationship between season of birth and long-term outcomes is still unclear (Buckles and Hungerman, 2013). Recent work by Deschenes et al. (2009), Wilde et al. (2014), and Isen et al. (2015) suggests that in utero exposure to high temperatures might be one causal explanation.

months (Levine, 1991; Dada et al., 2001; Chen et al., 2003; Svartberg et al, 2003; Meade and Earickson, 2000; Ellison et al., 2005). While these findings point toward hot weather as harmful to reproductive health for humans, other seasonal confounders hinder causal inference. Also, men with more sedentary occupations have lower sperm counts, potentially via increases in scrotal temperature (Henrik et al. 2002a; Henrik et al. 2002b).

Temperature shocks could also affect conception probabilities via changes in coital frequency. Extreme heat could raise physiological cost of coitus on a given fertile day, leading to a shift in coital frequency to some subsequent day(s) when the probability of conception conditional on coitus could be diminished.[7] Temperature could influence hormone production thereby affecting sex drives.[8] Alternatively, the behavioral response to a temperature shock could lead individuals to shift coitus to some fertile day(s) in a subsequent cycle either due to the discomfort from intercourse at higher temperatures or perceived changes in reproductive health due to the temperature shock. Also, individuals may time coitus based on expectations about future weather and their preferences to maximize infant health outcomes or minimize pregnancy costs.[9] Given our research design, our estimates only incorporate this channel to the extent current temperature shocks affect expectations about future shocks. The best evidence to support a causal link between temperature and coital frequency in humans comes from seasonal relationships, which are potentially biased by omitted factors.[10]

As another channel, temperature may affect time use and, in turn, impact mixing rates among potential sexual partners, especially if they spend more time indoors. Graff Zivin and Neidell (2014) provide indirect evidence to support this mixing-rate mechanism using data from the American Time Use Survey. They find that individuals substitute from outdoor activities to indoor activities at high temperatures. This could increase indoor contact and, in

[7] Among a sample of 221 healthy pregnant women intending to become pregnant, Wilcox et al. (1996) found the probability of conception was over 30% if intercourse occurred on the day of ovulation or up to 2 days prior. The probability of conception was closer to 10% 3 to 5 days before ovulation, and nil on other days. Of the successful conceptions, only two thirds ended in live births.

[8] Heat exposure led to a reduction in testosterone levels in both bulls and boars for two weeks (Rhynes and Ewing, 1973; Wettemann and Desjardins, 1979).

[9] Using the National Survey of Family Growth, Rodgers and Udry (1988) found that individuals report stopping contraception most often in June and July. If women assume they will conceive right away, these stopping times are consistent with expectations of April and May as the best time to give birth.

[10] Albeit in a small sample of women, Udry and Morris (1967) find that coitus dips in August in the United States. For adolescents, sexual debut occurs more often during the summertime, though school vacation complicates attributing this seasonality to temperature (Rodgers, Harris, and Vickers, 1992; Levin, Xu, and Bartkowski, 2003). Levin et al (2003) find a secondary debut in December among romantically linked couples.

turn, coital frequency provided adequate temperature control indoors. As part of our analysis, we extend the work of Graff Zivin and Neidell (2014) and explore impacts on reported "personal and private activities", which includes having sex, in the American Time Use Survey.

Temperature could also influence fertility through more indirect channels, though the effect on conception probabilities may be delayed. For example, temperature shocks could impact the agricultural sector, which could then affect fertility through delayed impacts on food prices, nutrition, or income. Using United States data between 1969 and 2011, Deryugina and Hsiang (2014) find that one weekday with temperatures above 86 °F reduces personal income by about $20 per year, the effect operating mostly through labor and crop productivity. In addition, temperature could impact disease transmission, like influenza (Shaman and Kohn, 2009; Barreca and Shimshack, 2012; Lowen and Steel, 2014), which could alter fertility.

Importantly, any change in conception probabilities in one cycle can affect the number of conceptions in future cycles via changes in the "susceptible population". That is, the population that failed to conceive in one cycle due to a temperature shock could shift conceptions to a subsequent cycle. More formally, 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 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*.

If conception probabilities were constant across cycles, conceptions would increase at a decreasing rate after the initial decline in conceptions. The rebound could be non-monotonic in the case of time-varying conception probabilities due to credit constraints or preferences for conceiving in certain calendar months. With constant conception probabilities, the cumulative rebound would asymptotically approach Δ_t.[11] Conversely, declining reproductive health with age could lead to a smaller cumulative rebound. 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

[11] 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.

$\Delta_t p_{t+1} + S_{t+1} dp_{t+1}$, 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 the sign and magnitude of dp_{t+1} is uncertain, the net effect on conceptions in cycle *t+1* is ambiguous.

In our study, we use *realized births in a given calendar month* to quantify the effects of a temperature shock that likely impacted conceptions several months prior. The exact timing will depend on the critical exposure period, the ex ante gestational length, and the time of exposure within the calendar month. A temperature shock that has an immediate impact on conception probabilities in a given month, henceforth referred to as "exposure month", will reduce births *approximately* 9 calendar months later followed by a rebound in births in the subsequent months.[12] If some individuals only engage in coitus during a specific calendar month, the rebound would manifest as an increase in births 21 months after the exposure month. A temperature shock could cause preterm delivery and increase births in the exposure month, while reducing births 1 month later. Fetal losses in the first month of pregnancy could manifest as a fall in births at 8 months and a rebound in births beginning at 10 months.

A handful of older studies have explored the temperature-fertility relationship using observational data (Siever 1985, 1989; Lam and Miron 1991b, 1996; Lam, Miron and Riley, 1994). Only Siever (1989) and Lam and Miron (1996) (hereafter LM) rely on variation in atypical temperatures thereby controlling for seasonal confounders. Neither of these existing studies comprehensively investigates the importance of dynamic adjustments, which is a key contribution of our work.[13] Siever (1989) uses data for the United States between 1950 and 1960 and correlates the effect of atypical monthly temperature on the birth rate 9 months later within each state. LM follow a similar approach to Siever, but use 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 Siever and LM's models are estimated separately by state, so statistical

[12] We assume a gestational length of 9 months for simplicity. Appendix Table A1 illustrates these four key simplified scenarios through which temperature shocks might impact realized births over a 24-month period (more details are provided in the note). See Lam et al. (1994) for a more formal fertility model.

[13] Although LM note testing for effects at 7, 8, and 11 months, these estimates are statistically insignificant and are dropped from the model. Siever (1989) tests 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. Siever concludes "the making up effect is essentially complete after 7 months" (p. 246). The confidence interval on this statistical test (not reported) is potentially large since the model is estimated separately by state and the data span 11 years.

precision and ability to flexibly control for time-varying cofounders is limited. And, these studies impose relatively strong functional form assumptions on the temperature-fertility relationship: Siever imposes a linear effect in monthly mean temperature, while LM use a quadratic in monthly mean temperature.

III. Data

Natality data. Birth counts are available at the state-by-month level from 1931 through 2010. The data come from three sources. We compiled state-by-month birth counts from historical Vital Statistics reports for the year 1931-1967,[14] machine-readable Natality Files for the years 1968 through 2004,[15] and the CDC's online National Vital Statistics System for the years 2005 through 2010. The monthly birth counts are defined by state of residence except for the 1931-1941 period, when only state of occurrence is available.[16] To our knowledge, these are the most expansive data ever compiled on monthly fertility outcomes for the United States.

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. [17] For the years 1931 through 1968, we estimate state-by-year populations by linearly interpolating between Decennial Censuses (Haines 2004). For the years 1969 through 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, though our results are robust to using birth rates in levels, the female population between 15 and 44 years of age in the denominator, or log of total births without adjusting for population size. Note that the 1968-2004 Natality data permit an exploration into information found on the birth certificate, like maternal age or birth weight of the infant. We present only a cursory analysis of these outcomes below in the appendix in the interest of conciseness. The Natality data have

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

[15] 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 relied on CDC's online National Vital Statistics System for the years 2005 through 2010.

[16] State of residence is the preferred measure since migration could be endogenous to temperature.

[17] Crude birth rates are typically measured on an annual basis per 1,000 population. We opt for scaling by 100,000 since we are constructing daily births rates at the month level.

information on date of last menses, which we use to 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). The GHCN have daily station information on minimum temperature, maximum temperature, and precipitation. The GHCN have geographic coverage across the continental United States over our sample period and include an impressive number of weather stations: there were 2,206 stations in 1930 and 4,969 stations in 2010 that consistently report daily weather conditions.[18]

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.[19] Importantly, we create the weather measures at the station-day level before aggregating to the state-month level to preserve non-linear effects.

We have humidity data from a separate data source, the Global Summary of the Day files. We control for specific humidity, which is reported in grams of water vapor per kilogram of air ("g/kg"). The humidity variable has poor coverage prior to 1945, so we only control for humidity as a robustness check. To the extent that humidity and temperature are naturally correlated, our temperature estimates incorporate some of the effects of humidity.[20]

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 approximately 4.7 daily births per 100,000 residents on average during our sample period. The unweighted annual average for the United States is 3.5 million total live births, ranging from 2.1 million births in 1931 to 4.0 million in 2010. Birth rates are lowest in Northeastern states

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[18] 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.

[19] 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.

[20] In a study on mortality, Barreca (2012) shows that failing to control for humidity causes little bias on the aggregate, but may be more important for estimating distributional effects across regions.

and highest in Southern states. The average temperature is above 80 °F approximately 4.7 days per month in the South, compared to only 0.6 days in the Northeast.[21] Although high temperature days and birth rates are positively correlated across regions, this positive relationship cannot be used to infer causal effects since many other socioeconomic factors, like 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. Panel A of 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 approximately 15% higher than April birth rates. The differences across regions also suggest that temperature plays a role in the timing of births, given the South is generally warmer than the rest of the United States. Other seasonal factors, like 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.

The fact that the seasonality is greatest in the South suggests that variation in the upper end of the temperature distribution might be a good predictor of birth seasonality. As a cursory test of this hypothesis, we compare the standard deviation in average births by calendar month to the standard deviation in average days with mean temperatures >80 °F by state. Panel B in Figure 1 illustrates that the two correspond closely. Overall, there is a strong positive relationship between these variables, with a correlation coefficient of 0.7. For example, Louisiana has the greatest variability in seasonal birth rates and among the greatest variability in the number of >80 °F days. Further, many of the states with standard deviations in average log births greater than 0.04 (the average) are located in the relatively warm Southeast and Southwest United States (e.g., TX, MS, FL). The relationship between the standard deviation in birth rates and *average* temperature is less pronounced (not reported), which motivates the need to flexibly modeling temperature to account for non-linear effects.

[21] Note that for station-days with an average temperature above 80 °F, close to 75% of these station-days have a maximum above 90 °F. Thus, we emphasize that a mean daily temperature above 80° F is very hot.

IV. Methodology

To identify the effect of temperature fluctuations on the birth rate, our model relies on plausibly 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) and Barreca et al. (2016) who analyze similar vital statistics data:

$$(1)\ \ Y_{st} = \sum_{j}^{J}\sum_{k}^{K}\beta_k^j\, TEMP_{s,t-k}^{j} + \sum_{k}^{K}\gamma_k\, X_{s,t-k} + \alpha_{sm} + \delta_t + \theta_{sy} + \pi_s^1 * t\ + \pi_{sm}^2 * t^2 + e_{st}$$

where *Y* is the log of the birth rate in state s at year-month t. *X* is a vector of precipitation controls.[22] α_{sm} is a state-by-calendar-month fixed effect to help ensure our model is 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-month determinants of the birth rate, such as seasonal employment. Year-by-calendar-month fixed effects (δ_t) control for time-varying factors that are common to all states, like 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.

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 are <30, 30-40, 40-50, 50-60, 70-80, >80 °F, with 60-70 °F 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, …, 24). We also

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

estimate the impacts on births 1 to 3 months prior (denoted by the index k=-3, -2, -1) as a placebo check since the temperatures were realized after delivery and should not affect prior birth rates. In sum, we have six temperature variables estimated over 28 months (3 placebo months + 25 treatment months).

As a robustness check, we also test for impacts using a polynomial spline in the daily mean temperature, with knots at 10, 30, 50, 70, and 90 °F. We use diurnal temperatures in place of daily mean temperatures as a test of intra-day temperature extremes. For example, a day with a maximum of 90 and a minimum of 80 might affect fertility outcomes differently than a day where the maximum was 100 and the minimum was 70, despite both having the same daily mean temperature.[23] We also include a set of humidity controls in one specification check.

While 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, this model's estimates are systematically shifted in the negative direction including the placebo months (-3, -2, and -1) where 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 Appendix Figure A1).[24] 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. 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). As illustrated in Appendix Figure A2, 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.

V. Results

Core results. Figure 2 reports the effects of one >80 °F day relative to one day in the 60-70 °F temperature bin on the log birth rate across the full set of exposure months using our core

[23] We linearly interpolate diurnal temperature using the daily maximum and minimum.

[24] As illustrated in Appendix Figure A1, the fraction of days above 80 °F increases relatively more in the South after 1980. Conversely, there were differential trends in birth rates across regions after 1980.

empirical model (equation 1). We control for the full set of temperature bins, though we focus on the effects of >80 °F days here. The estimates indicate each additional >80 °F day causes birth rates to fall by approximately 0.06% 8 months later, 0.40% 9 months later, and 0.21% 10 months later, all statistically significant at the five-percent 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 are meaningful: the effect size at month 9 implies a reduction of 1,150 fewer births across the whole United States for *each* >80 °F day, on average over our sample period.[25]

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 later (i.e., 8 or 9 calendar months later) since most fertile days fall between 10 and 20 days after the start of the menses (Wilcox et al., 1996; Fehring et al., 2006). If the critical exposure period was around the time of conception, then there should be virtually no decline in births at month 10 since few births last longer than 41 weeks.[26] Instead, the coefficient is approximately half the magnitude (0.0021 vs. 0.0040). It is possible the fall in births were made up disproportionately of births with atypically long gestational lengths. However, Appendix Table A2 rules out this possibility using information on gestational length in the Natality Data for the years 1968-2004.[27] More plausibly, exposure to high temperatures has a delayed effect on conception rates. In Section VII, we show support for the second hypothesis and explain why this evidence suggests that the initial decline in births is due to worse reproductive health as opposed to decreased coital frequency.

We 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 the cumulative effect of a temperature shock over months 8-10 is a decrease of

[25] The average (unweighted) number of monthly births over our sample period is 295,000.

[26] We may potentially observe an *increase* in births if the affected population becomes susceptible to conceiving in the month immediately following the temperature shock

[27] We observe a statistically significant 0.014 percentage point decrease in the probability of >41 weeks gestation among births at 10 months, which is consistent with the expected draw from the distribution of gestational lengths. The average probability for our sample is 10.3% and we observe a 0.2% decline in births at month 10. So, we would expect a decline of approximately 0.02 percentage points if one tenth of the 0.2% decline was made up births of >41 week gestations. Information on gestational length is limited in the Natality data prior to 1981. Gestational length is missing in 40% of births in 1969, 22% in 1980, but only 6% 1981.

0.0067 log points, while 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). Note that the majority of the secondary rebound (0.0008 log points) occurs between months 19-21 (jointly statistically significant), suggesting a segment of the population may have preferences for conceiving or engaging in sexual activity in certain calendar months. In sum, the rebound in months 11-13 offsets 31% (0.0021/0.0067) of the decline in months 8-10, and months 14-24 offset an additional 18% (0.0012/0.0067), bringing the cumulative rebound to nearly 50%. The effect size over months 8 through 24 imply a reduction of approximately 970 fewer births for each >80 °F day on average across the whole United States over our sample period.

We also present novel evidence that temperature shocks reduce gestational lengths by one month. One >80 °F day causes a statistically significant 0.03% increase in birth rates in the exposure month (month 0) and a 0.06% decrease one month later (month 1). The larger magnitude of the month 1 coefficient is suggestive that temperature shocks may cause fetal deaths near the end of some pregnancies. However, we cannot reject the possibility that the coefficients at month 0 and month 1 are equal in absolute value (p=0.149). Importantly, our estimates for the placebo months (-3, -2, -1) are statistically insignificant and near zero. Thus, our model appears to be reasonably free of biases from spurious time trends.

Figure 3 Panel A 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. Though we report only the effects at 9 months here, we control for the full set of exposure months. Identical by design to Figure 2, we observe a large and statistically significant decrease in birth rates from exposure to one >80 °F day. Each 70-80 °F day also reduces birth rates 9 months later, but to a lesser degree than >80 °F (0.14% vs. 0.40%). Colder temperatures below the omitted 60-70 °F category have little impact on birth rates 9 months later. The effect of <30 °F in other exposure months is also minimal (see Appendix Figure A3).

Figure 3 Panel B illustrates the importance of accounting for non-linear effects in the temperature-fertility relationship. We compare our core model estimates to estimates from a model with identical controls but with a quadratic in monthly mean temperatures in place of daily temperature bins, similar to previous research. The comparison is not so straightforward since the marginal effect of a one-day change in temperature is conditional on the monthly mean temperature in the quadratic monthly model.[28] Nonetheless, the quadratic monthly model shows that a monthly mean shift in temperatures from 65 to 85 °F would result in a 7% decline in births 9 months later. Conversely, our binned model implies 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 indicates that temperatures below 60 °F have no effect on birth rates relative to 60-70 °F. 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 failing to capture a tipping point around 70 °F.

Robustness Checks. The main results in Figures 3 and 4 are robust to different model specifications, as shown in Appendix Figures A4 – A8. We show estimates using birth rates in levels and using the population of women 15-44 as the denominator in our birth rate measure (Appendix Figure A4). We find similar effects using *diurnal* temperature bins that captures the frequency of time (not days) within a given 10 °F bin, with temperatures above 90 °F and below 0 °F as the categories at the bounds (Appendix Figure A5). We show the estimates using a spline in daily mean temperature (Appendix Figure A6). The spline model estimates are quite similar to the binned model. However, the spline predicts larger effects at temperatures past 85 °F, which has implications for assessing the costs of large increases in the temperature distribution with climate change. Appendix Figure A7 illustrates the estimates from two models: one without the state-year fixed effects and one without state-by-month quadratic time trends. As noted in Section IV, the state-by-year effects help address a potentially spurious correlation between declining fertility rates and increasing temperatures after the 1970s.

We estimate the effects of temperatures and humidity in Appendix Figure A8. One "high humidity day" above 18 grams of water vapor per kilogram of air (g/kg) leads to 0.2% decrease in births 9 and 10 months later.[29] The estimated effects of hot temperatures are slightly

[28] 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 existing studies that use average monthly temperature (Siever 1989 and LM) is also complicated by the fact their models are 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 to 85 °F, in a month with mean temperatures of 65 °F, would reduce birth rates 9 months later by 0.17%, which is less than half the magnitude of our estimate.

[29] We model humidity using 2 g/kg bins with 8-10 g/kg as the omitted category, 0-2 g/kg as the lowest bin, and above 18 g/kg as the upper bin. Note the average state experiences 3 days per year above 18 g/kg.

diminished (relative to Figure 2), suggesting that humidity is one natural mechanism through which temperature impacts birth rates. The inclusion of humidity causes the effect at month 9 to decline from 0.4% to below 0.3%. Like low temperatures, low humidity levels are not a strong predictor of birth rates (results not reported). Given the positive association between influenza and low humidity levels found in recent epidemiological studies (Shaman and Kohn, 2009; Barreca and Shimshack, 2012), we can rule out influenza as a primary mechanism.

Appendix Table A3 estimates a model that better captures the effects of "heat waves", or consecutively hot days. Using a more parsimonious model with only exposure months 8-13, 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", defined as a span of 3 or 5 consecutive hot days. This implies that hot days have an additive effect within short time spans. Appendix Table A4 estimates a model with each month separately as a check to ensure that our core model is not over-controlling for weather to the extent that hot days are naturally serially correlated. The estimates are only slightly larger in absolute value implying that any over-controlling bias is minor relative to the benefit of controlling for serial correlation in observed weather.

Explaining the seasonality in births. The estimates from our empirical model predict much of the seasonality in births in the United States. We take our core model estimates (Figure 2 Panel B) and apply them to the observed distribution of temperatures over our sample period. Figure 4 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 overestimate births in October through January, which may be partially explained by the December holidays causing a forward displacement in conceptions.[30] That said, the model still explains nearly half of the variance (R^2 = 0.49) when correlating 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.[31]

[30] Factors that are fixed across seasons, such as holidays, disease, nutrition, and expectations about the weather most likely contribute to the seasonal birth patterns observed in the United States. However, these fixed factors are controlled for in our model, so they do not pose a threat to our identification strategy. Rather, they are other important determinants that account for the unexplained variance in seasonality.

[31] The R^2 is 0.44 in a model that has quadratic in monthly mean temperature for the full set of months.

Panel B shows the model also predicts substantially more seasonal variability in the South relative to the rest of the United States, consistent with the actual seasonality across regions (Figure 1).

One implication from this prediction is that high temperatures at conception could lead to worse infant health outcomes by the merely shifting births from the spring to summer months. As noted by Currie and Schwandt (2013), infants conceived in the summer and born in the spring tend to have better health outcomes than those infants conceived in the fall and born in the summer. The exact reasons underlying this relationship is unclear, but Currie and Schwandt (2013) find that the effects persist even when controlling for mother fixed effects. For the same mother, August conceptions have birth weights that are 10 grams higher than November conceptions on average (Currie and Schwandt, 2013).

Deschenes et al. (2009) suggest that in utero exposure to high temperatures could be one mechanism through which summer conceptions are healthier than fall and winter conceptions. According to their analysis, each additional day above 85 °F in the third trimester reduces birth weights by approximately 0.01 percent. During our sample period, moving from a May birth to an August birth exposes infants to approximately 21 more >80 °F days in the third trimester. Taking the coefficient from Deschenes et al. (2009), this implies that shifting a birth from May to August birth could reduce that child's birth weight by a modest 0.2% on average, or about 6 grams.

Implications for climate change. The fact that we fail to observe a full rebound in the short term suggests that temperature increases from climate change could reduce cumulative birth rates. Given the non-linear relationship observed above, we focus on the costs of the increase in >80 °F days for simplicity. We find that each hot day reduces cumulative birth rates by about 0.0033 log points over months 8 through 24. The Hadley CM3 climate model, which is commonly used for climate projections, projects about 60 more >80 °F days by the end of the century if greenhouse gas emissions continue unabated (Barreca et al., 2016). This suggests that the increase in >80 °F days alone will lead to about 1.7% fewer births per year (60 days x 0.0033 monthly effect / 12 months). While statistically significant, this projected impact appears relatively small compared to the 50% decline in the birth rates in the United States since the 1950s (Appendix Figure A1).

Further, we caution from interpreting this back-of-the-envelope calculation literally for two reasons. First, our model is identified from unusual temperature shocks and does not account for adaptive investments that could be made in response to changes in expectations in the long term. Second, our model does not capture any rebound in births that may occur past month 24. Both of these caveats imply our calculations likely overstate the negative effect of climate change on completed fertility. However, small expected changes in completed fertility mask potentially larger effects on infant health.

Climate change is likely to adversely affect infant health more than previously anticipated in past research due to more infants to be born during the late summer and early fall. Using the Hadley CM3 model, we project nearly 5% more births in the late summer and early fall relative to spring. (See Appendix Figure A9 for more detail.) Second, the cost of this shift in birth month will expose infants to considerably higher temperatures during the third trimester. A shift in birth month from May to August at the end of the century will expose an infant to 49 additional days >80 °F in the third trimester.

VI. Exploring the Role of Adaptation

Next, we restrict the model to exposure months 8 through 13 in order to improve statistical power and facilitate exposition of the results. All other controls are identical to our core model (equation 1). We focus on the effects of days above >80 °F, though our model controls for other temperature bins. Table 2 Panel A illustrates that the main estimates on >80 °F days in months 8 through 13 are unchanged using the narrower set of exposure months. Below, we explore how the effect of >80 °F days vary by climate and time 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 the magnitude of the effects in months 8 through 10 are all smaller in states with warmer climates. The difference between 'cold' and 'hot' states at 9 months 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). Similarly, the hot-cold state differences in the coefficients at 8 and 10 months correspond to gaps of 50% and 40%, respectively. 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, like wealth, accounts for some of the heterogeneity across hot and cold states.

Heterogeneity over time. We first test for differences in the temperature-fertility response function by time period. Table 2 (Panel C) revisits the effects of each >80 °F day by exposure month between the 1931-1969 and 1970-2010 periods. Here, we use the full set of years in our sample, but interact our temperature variables with an indicator for the time period. The estimates for months 9 through 13 are much smaller in the later period, with the differences being statistically significant. For example, the effect of one >80 °F day on birth rates 9 months later falls by roughly half, from 0.54% to 0.31%, over this time period. The cumulative effect over months 8 through 13 falls from 0.49% to 0.39%, suggesting that fertility costs may be greater in countries at earlier stages of economic development.

Figure 5 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 only present the marginal effects of each additional >80 °F day on log birth rates 9 months later, though 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 9 months later. The effect size monotonically decreases after the 1960s. By the 2000s, one additional >80 °F day causes the birth rate 9 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 due to random measurement error in temperature assignment since the data are reported by state of occurrence. This dampening of the temperature-fertility relationship follows the changes in air conditioning usage over the same time period (see Appendix Figure A10).

The role of air conditioning. We explore whether residential air conditioning (AC) can explain this decline 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 assumed to be zero in 1950.[32] We use the growth rate in AC coverage between 1970 and 1980 to project out to 2010, while capping the coverage at 100%.[33] Our work builds on Siever (1989), which correlated changes in air conditioning between 1960 and 1980 with changes in birth seasonality. We extend Siever'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.

Note that we take two steps to account for the possibility that the adoption of air conditioning is correlated with time-varying omitted factors that may also impact 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 air conditioning coverage correlates with secular trends in vulnerability to temperature extremes.

We find that the diffusion of air conditioning substantially mitigated the temperature-fertility response function, especially the effect of 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).[34] Positive and statistically significant AC coefficients at 8, 9, or 10 months would imply that AC mitigates temperature's influence around the time of conception. Indeed, the effect on the AC interaction term is positive and statistically significant at 9 and 10 months. A 50-percentage point increase in air conditioning coverage reduces the impact at 9 months by 0.1 percentage points in absolute terms (0.5 x 0.00192). We do not observe a statistically significant dampening of the rebound in months 11, 12, and 13, though we cannot rule out meaningful effect sizes.

Next, Table 3 Panel B adds controls for other interactions with factors that may have contributed to historical changes in the effects of high temperature on birth rates. We add

[32] We define "air conditioning" as at least one air conditioning unit or central air conditioning.
[33] Appendix Figure A12 illustrates the estimated AC coverage by region. See Biddle (2009) 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.
[34] The interaction between temperature and AC is small and statistically insignificant at colder temperatures, further supporting the presumed temperature control mechanism provided by AC.

temperature interactions with state-year measures for the fraction of women with 12 or more years of schooling, access to legal abortion, and unmarried women's legal access to the birth control pill before age 21 (Bailey, 2006; Goldin, 2006; Goldin and Katz, 2002; Guldi, 2008; Levin, Kane, Staiger, Zimmerman, 1996).[35] We explore impacts by fraction of workers with "high risk" of exposure to ambient temperatures using data from the census, with the inter-census years being interpolated.[36] We test for interactions with the fraction of the population with electrification using data from Barreca et al. (2016), and with interactions with log income using data from the Bureau of Economic Analysis.

After accounting 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 (0.00192 vs. 0.00225 log points). The effect at month 10 is no longer statistically significant, though the magnitudes are similar across Panel A and Panel B. The interaction coefficients on the other modifier variables are statistically insignificant in months 9 and 10. Although we do not find definitive evidence that these factors were important contributors to the dampening of the temperature-fertility relationship, our findings do not refute their role in the dramatic decline in birth rates that began in the late 1950s.

To demonstrate the magnitude of the AC estimates, we note that the diffusion of AC can account for about one third the change in the temperature-fertility relationship between 1950 and 2010. As noted above in Figure 5, the effect of one >80 °F day on birth rates 9 months later fell from 0.006 log points in the 1950s to about 0.002 log points by the 2000s. The estimated AC coverage increased from 5% in the 1950s to 87% in the 2000s. As such, the change in AC causes the effect to fall by 0.0016 log points (0.82 x 0.002 log points), or about one third of the 0.004 log point decline.

[35] We focus on variation in the legal access to the "Pill" to unmarried women under 21 because it occurred in the 1970s. Married women gained legal access to the Pill in the early-to-mid 1960s (Bailey, 2010). The visible dampening of the temperature-fertility relationship began in the 1960s and continued through the 2000s (Figure 5), so the *introduction* of the Pill in 1960 is not likely to be an important omitted variable, though utilization could be changing over this time.

[36] Following Graff Zivin and Neidell (2014), we define high-risk employment as agriculture, forestry, fishing, hunting, mining, construction, manufacturing, transportation, and utilities.

VII. Exploration into Mechanisms

Impacts on Time Use (2004-2010). Using the American Time Use Survey (ATUS) between 2004 and 2010, we are able to explore how temperature might affect sexual activity. These data come from self-reported daily surveys from individuals who are exiting the Consumer Population Survey. The ATUS has information on state of residence and date of interview, which we use to match with our weather variables at the state-day level.[37] We focus on individuals who are between 18 and 45 years old, and stratify our estimates by marital status. The main outcome of interest is whether the individual spent any time in "personal or private activities", which includes "cuddling partner in bed, having sex, making out, necking, personal activity (unspecified), private activity (unspecified), and spouse gave me a massage (2007+)".[38]

We estimate the following empirical model:

$$(2)\ \ Y_{sd} = \sum_{j}^{J} \beta^j\, TEMP_{s,d}^{j} + \gamma\, X_{s,d} + \alpha_{sm} + \delta_d + \theta_{sy} + e_{st}$$

where *Y* is the fraction of people in state s and year-day d reporting any personal or private activities. *TEMP* is the set of temperature bins and *X* is a vector of precipitation controls for the year-day d.[39] We include state-by-month fixed effects (α_{sm}), year-day fixed effects (δ_d), and state-by-year fixed effects (θ_{sy}) to help ensure our model is identified from random daily fluctuation in the distribution of temperatures.

Figure 6 illustrates that each additional >80 °F day *increases* the probability that unmarried individuals engage in any personal or private activity on that day. The effect is a statistically significant 1.0 percentage point increase, which is large relative to the average of 0.8 percent for this population. There is no statistically significant effect among married individuals, though large confidence intervals preclude ruling out meaningful impacts in either direction. To investigate for potential biases from misreporting, we explore whether temperature affects the probability the respondent refused to respond or answered that an activity is "none of your business". Appendix Figure A11 shows that the likelihood of such a

[37] We conduct our analysis at the state-level since finer geographic detail is only available for those individuals living in metropolitan areas with over 100,000.
[38] The ATUS have data for 2003, but we omit this year since "using the bathroom" is included in the category.
[39] We control for the fraction of days in the month t-k with between 0.01 and 0.50 inches and above 0.50 inches. The omitted category is the fraction of the month with no precipitation.

response increases on hot days as well, providing further support that the estimated relationship between hot days and sexual activity, at least for unmarried individuals, is likely positive.

Impacts on conception-survival rates (1969-2003). As noted above, hot days cause a relatively large reduction in births 10 months later, suggesting 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 date of last menses, which can be used to infer date of conception. We assume that conception occurs two weeks after that start of the last menses and the mother's state of residence at the child's birth is the same as the state of residence at conception.[40] For this analysis, the unit of observation is at the state and year-week of conception. Given we only observe those conceptions that survive to birth, our analysis cannot distinguish between fetal losses and decreases in conceptions. 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.[41] We exclude 1968 and 2004 conception years from our sample since 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.[42]

We estimate the following model:

$$(3)\quad Y_{st} = \sum_{j}^{J}\sum_{k}^{K}\beta_k^j\,TEMP_{s,t-k}^j + \sum_{k}^{K}\gamma_k\,X_{s,t-k} + \alpha_{sw} + \delta_t + \theta_{sy} + e_{st}$$

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-week t-k. We also control for state-by-week fixed effects (α_{sw}), year-by-week dummies (δ_t), and state-by-year fixed effects (θ_{sy}) to help isolate exogenous changes in temperature.[43] We allow temperature effects for up to 6 lagged weeks and 6 forward weeks (i.e., k=-6, -5, … 6) to identify the critical exposure period.[44]

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[40] Fehring et al. (2006) surveyed 141 women between 3 to 13 cycles each and found that "ninety-five percent 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".

[41] 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 SEER and assigned at the state-year level.

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

[43] We partial out the state-by-week fixed effects prior to estimation to reduce the computational burden.

[44] Unlike above, temperature shocks could affect conception rates after the fact, i.e. there is no placebo check.

The estimates in Figure 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 same week (week 0). One >80 °F day two weeks prior to the estimated week of conception reduces the conception-survival rate by a statistically significant 0.6%. The coefficient at week 4 and 6 indicates that each hot day four and six weeks *after* conception reduces the conception rate by 0.1%, potentially due to fetal losses.[45] Panel B drop data where the menses is reported to be on the 1st, 5th, 10th, 15th, 20th, 25th, 28th, or 30th of the month where there is heaping in the data, possibly due to measurement error. The estimates in Panel B are qualitatively similar. Taken with the time-use analysis above, these estimates suggest we can rule out high temperature causing an *immediate reduction* in sexual activity.[46] The next most likely explanation is that temperature harms reproductive health prior to conception.

Weekday versus weekend, and Daytime versus Nighttime exposure. We explore how the effects vary by exposure on the weekend (Friday through Sunday).[47] Table 4 Panel A illustrates the effects from a model that includes exposure months 8 through 13 and interacts our core temperature variables with an indicator for weekday and weekend. The estimates are similar across weekday and weekend, which suggests we can rule out exposure at work or weekend behavior as the main mechanisms. One implication is that the critical time of exposure is in the evening, when exposure might be relatively similar throughout the week. This interpretation is supported by previous work showing that scrotal temperatures were higher at nighttime (Henrik et al. (2002a).

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. We include minimum temperature bins <30, 30-40, 40-50, 50-60 (omitted), 60-70, and >70 along with maximum temperature bins <40, 40-50, 50-60, 60-70, 70-80 (omitted), 80-90, and >90. Indeed, we find that minimum temperature is a stronger predictor of birth rates than maximum temperature. Table 4 Panel B illustrates the parameter estimates on minimum temperatures

[45] This could help explain the drop in births 8 months later that we observe in our main analysis (Figure 2).
[46] Temperature could also affect sexual activity some weeks into the future through some indirect channel, e.g., income. However, when we estimate impacts on personal or private activities in the ATUS using a 15-day moving average, we do not find a statistically significant decrease in such behavior.
[47] The results are similar when we define the weekend as Saturday and Sunday only.

above 70 °F and maximum temperatures above 90 °F. The magnitude of the minimum temperature >70 °F effect is much larger than the maximum temperature >90 °F effect (0.37% versus 0.11%). The joint F-statistic for the minimum temperature variables is 155.6 relative to 18.0 for maximum temperature. Like the weekday-weekend analysis above, this suggests that the critical exposure period may be at nighttime. However, we cannot rule out the possibility that we are incorporating the effect of some other weather phenomenon, like humidity, by controlling for both minimum and maximum temperature in the same model.

Testing for Fetal Losses (1968-2004). Prior research shows that male fetuses are more vulnerable to in utero health shocks (Trivers Willard, 1973; Sanders and Stoecker, 2015). Using the 1968-2004 Natality, Appendix Table A2 presents the marginal effect of one additional >80 °F day on the probability of female birth across months 8 through 13. We observe a modest but statistically insignificant increase in the probability of female births at month 8, providing suggestive evidence that the decline in births in month 8 is due to fetal losses at the very early stages of the pregnancy. As further support, Appendix Table A2 shows that >80 °F reduces the probability of low birth weight 8 months later. Taken with the increase in female births at month 8, this improved health suggests fetal losses among unhealthier fetuses early into the pregnancy.[48] The estimates in other months are less informative.

Testing for Maternal Selection and Heterogeneity by Age (1968-2004). One hypothesis is that the observed decline in births in months 8-10 is comprised of relatively more low SES mothers either due to greater vulnerability or the fact that these groups are more likely to engage in unprotected sex without intention of conceiving. We test this hypothesis in Appendix Table A2 using Natality Data between 1968 and 2004. We have chosen outcomes on the birth certificate that reflect lower socioeconomic status (SES), including: mother has less than high school education, mother is non-white, and father's age is missing from birth certificate, a proxy for paternal support. Overall, the evidence suggests that low SES mothers are only *slightly* more

[48] Unlike the effect at month 8, extreme heat correlates with an increase in low birth weight in months 9 and 10. The lower birth weight in months 9 and 10 could be a lasting causal impact on fetal health or a selection effect. Though we cannot definitively differentiate between the two, the analysis of maternal characteristics suggest that, if anything, birth outcomes should improve in months 9 and 10. The fact that we observe worse outcomes supports the possibility of a causal impact on health.

vulnerable to high temperatures. For example, each >80 °F day leads to a 0.025 percentage point reduction in the probability that the mother is non-white at 9 months.[49]

We also explore how the impacts on birth rates vary by maternal age in Appendix Table A5 using Natality data for the years 1968 through 2004. We group mothers in 5-year age groups, 15-19, 20-24, 25-29, 30-34, 35-39, and 40-44. The initial decline in births at months 9 and 10 is qualitatively similar across the age groups, though somewhat larger for women between 40 and 44. However, we find that the rebound is smaller for the 15-19 and 35-39 age groups and *much* smaller for the 40-44 age group. As discussed in Section II, the smaller rebound for mothers 15-19 years old could be explained preferences for sexual activity during summer break from school. The smaller rebound for women over 35 years old is consistent with the hypothesis that reproductive health declines with age. Though, we cannot rule out the possibility that women 35 and over also have preferences for coitus in certain calendar months. Nonetheless, the smaller rebound highlights that the costs of temperature shocks can have a meaningful impact on total completed fertility for this older group.

Urban vs. rural counties (1968-1988). We estimate the effects by metropolitan status of the county using county identifiers in the publicly available Natality Data for the 1968-1988 period. County is not available from 1989 on in the publicly available data. The unit of observation is at the state-year-month-metro status level in this analysis. We first match births and weather in a given county-year-month. In order to address zero births in smaller counties and reduce computing costs, we then collapse the data to the state-year-month-metro status level, where the metro status is an indicator for whether the county was designated as metropolitan in the 1988 Natality Data. The controls are similar to our main model, except we include year-month fixed effects as main effects and interacted with metro status and state-by-calendar-month fixed effects as a main effect and interacted with metro status. As shown in Appendix Table A6, the estimates are only slightly larger in absolute value in non-metropolitan

[49] Our findings regarding maternal characteristics are somewhat different, though not in conflict, with recent work by Buckles and Hungerman (2013) (hereafter BH). BH explored the role of maternal selection in differences in outcomes across season of birth. They conclude weather at the time of birth is a better predictor of seasonality in maternal characteristics than weather at conception, which differs from our findings. However, BH's model is partially identified from some fixed differences in seasonality across counties, while our model focuses on plausibly random variation in temperatures.

counties and the difference is not statistically significant. Thus, differences across urban and rural counties do not appear to be a major cofactor in the temperature-fertility relationship.

VIII. Conclusion and Implications for Climate Change

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, followed by a partial rebound in birth rates at 11, 12, and 13 months. Our study offers four important lessons for climate change. First, we find evidence that high temperatures reduce fertility through worse reproductive health rather than diminished sexual activity. As such, the potential to mitigate the impacts of temperature shocks due to climate change via a purely behavioral response seems to be limited.

Second, climate change could exacerbate the already "below-replacement" birth rates in the United States and similar developed countries. The Hadley CM3 model projects an additional 60 hot days by the end of the century. The exact magnitude of the decline in birth rates due to this climate change is difficult to quantify given our estimates are identified from unusual temperatures and individuals could likely make adaptive investments to mitigate effects of climate change. Nonetheless, our estimates suggest this increase in hot days alone would only imply a modest 2% decline in birth rates, or about 80,000 fewer births per year on a baseline of 4 million births. We find that temperature shocks have a more lasting impact on birth rates for women 35 and older, so climate change's impact could be exacerbated by the trend toward giving birth at later ages (Mathews and Hamilton, 2016). While an important cost, the magnitude of the effect is likely small relative to the fertility effects of other socioeconomic changes that could result from climate change, like migration.

Third, the projected increase in temperatures will raise the cost of conceiving during summer months and increase the proportion of conceptions in the fall and winter, leading to more summer births and worse infant health outcomes. As noted by Currie and Schwandt (2013), infants conceived in the summer months tend to have better health outcomes, like higher birth weight, than those conceived in the spring. The causal mechanisms underlying this relationship are not well established given concerns over maternal selection (Buckles and Hungerman, 2013; Currie and Schwandt, 2013). However, results from Deschenes et al. (2009) suggest that exposure to hot days in the third trimester may be responsible though the effect size is relatively small. As with other early-life health shocks, recent evidence suggests there may be long-term consequences to this increased in utero exposure to high temperatures (Wilde et al., 2014; Isen et al., 2015).

Fourth, our historical estimates suggest that climate change could have even larger impacts in developing countries, especially those with limited access to air conditioning. We document a large reduction in the temperature-fertility relationship over our 80-year sample period and find that air conditioning can explain one third of the dampening of this relationship over time. Echoing a recent study on mortality (Barreca et al., 2016), providing low-cost access to air conditioning may be an effective tool for mitigating the fertility costs of climate change throughout the world. However, the costs of increased air conditioning usage include increased greenhouse gas emissions, underscoring the fundamental dilemma in mitigating climate change impacts using energy-intensive technologies.

In addition to these insights regarding climate change, this research helps resolve some of the debate regarding the major determinants of birth seasonality. Our dynamic estimates predict nearly half the seasonal variance in birth rates in the United States. We show that models that fail to account for the rebound in births can only account for one quarter of the seasonal variance. While our novel findings suggest that temperature is likely the single-most important determinant of birth seasonality in the United States, other environmental factors, like sunlight (Trudeau et al., 2016), may still have a large influence on birth seasonality and are worthwhile of exploration. Furthermore, more research is needed to assess how temperature might influence birth seasonality in other parts of the world, including developing countries.

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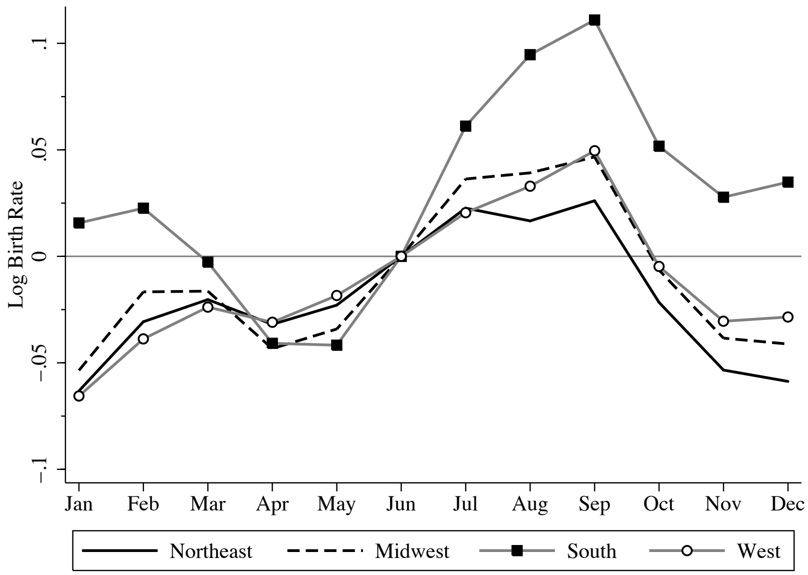
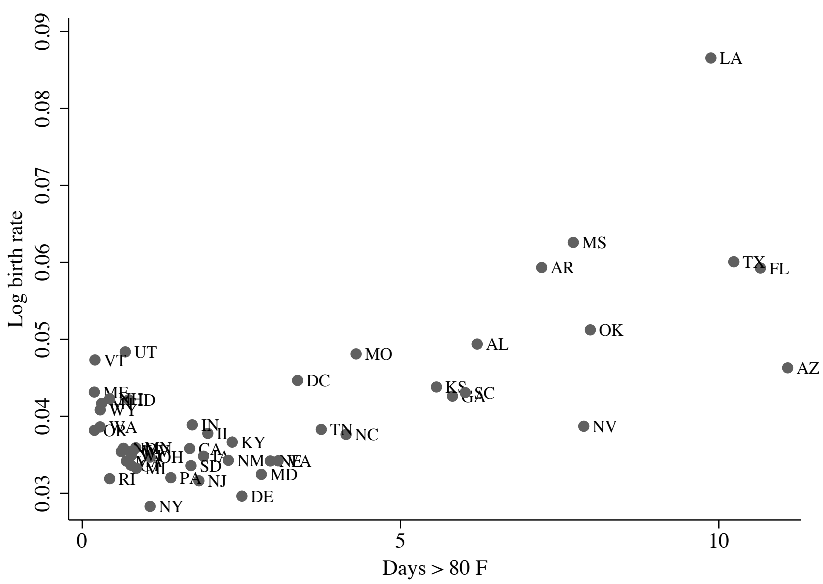
Figure 1: Seasonality in Daily Birth Rate per 100,000 Residents, 1931-2010

Panel A: Differences by census region and calendar month

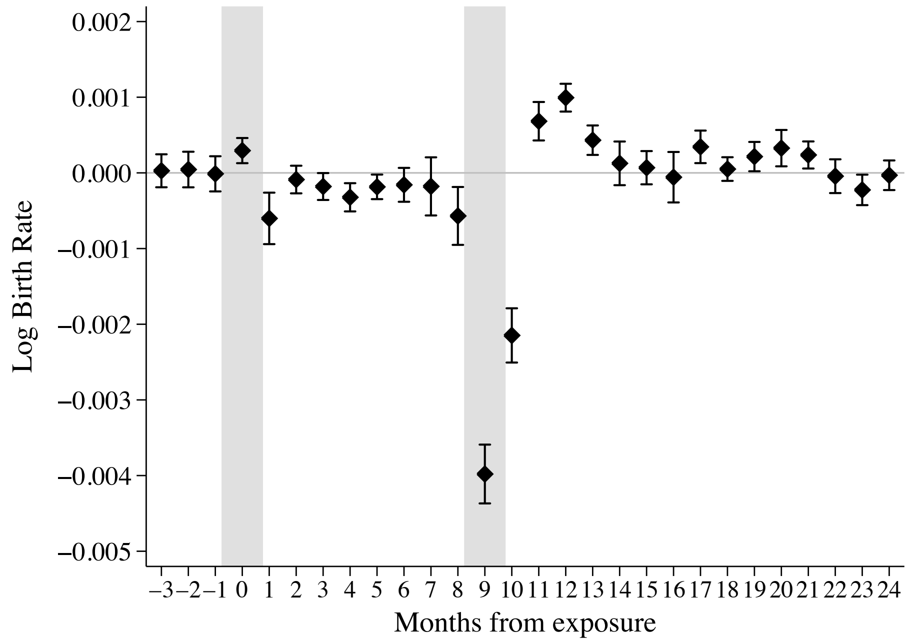


Panel B: Standard deviation in birth rates and standard deviation in days above 80°F



Note: Calculations use state-year populations as weights. To arrive at Panel B statistics, we first average log births and days above 80 °F for each state and month. We then calculate the standard deviation over the calendar year by each state.

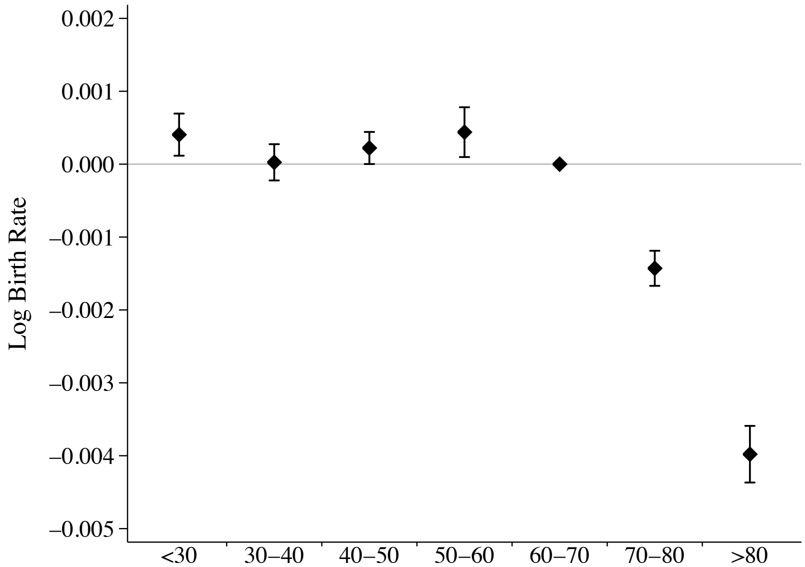
Figure 2: Estimated Temperature-Fertility Relationship: Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate, by Months from Exposure



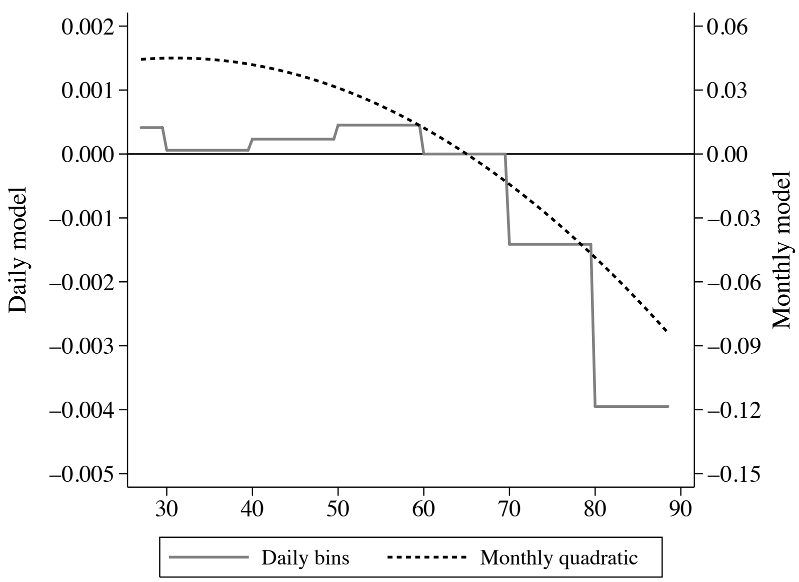
Note: The diamonds are the point estimates and the brackets represent +/- two standard errors. The estimates can be interpreted as the impact on the log monthly birth rate, in log points, of one additional day with a mean temperature >80 °F relative to 60-70 °F . The model has year-month fixed effects, 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 over 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.

Figure 3: Estimated Temperature-Fertility Relationship: Effect of Daily Mean Temperatures on Log Birth Rate 9 Months Later

Panel A: Core estimates with standard errors



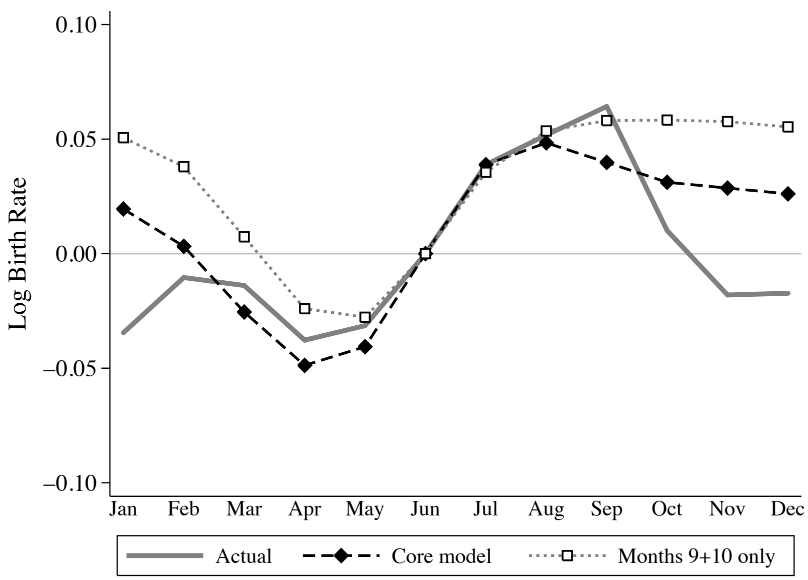
Panel B: Comparison with monthly quadratic model



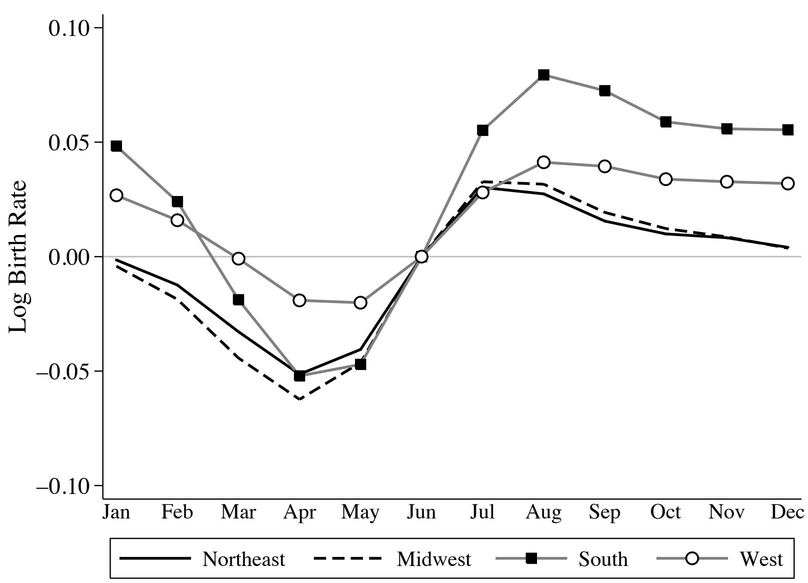
Note: In Panel A, the diamonds are the point estimates and the brackets represent two standard errors around the point estimates. In Panel B, the "daily bins" model refers to our core model. See note to Figure 2 for details on that model. The "monthly quadratic" model has identical controls to our core model and the same number of lags and leads, except temperature is a quadratic function of the monthly mean temperature.

Figure 4: Model Predictions of Log Birth Rate

Panel A: Predictions vs. actual, United States

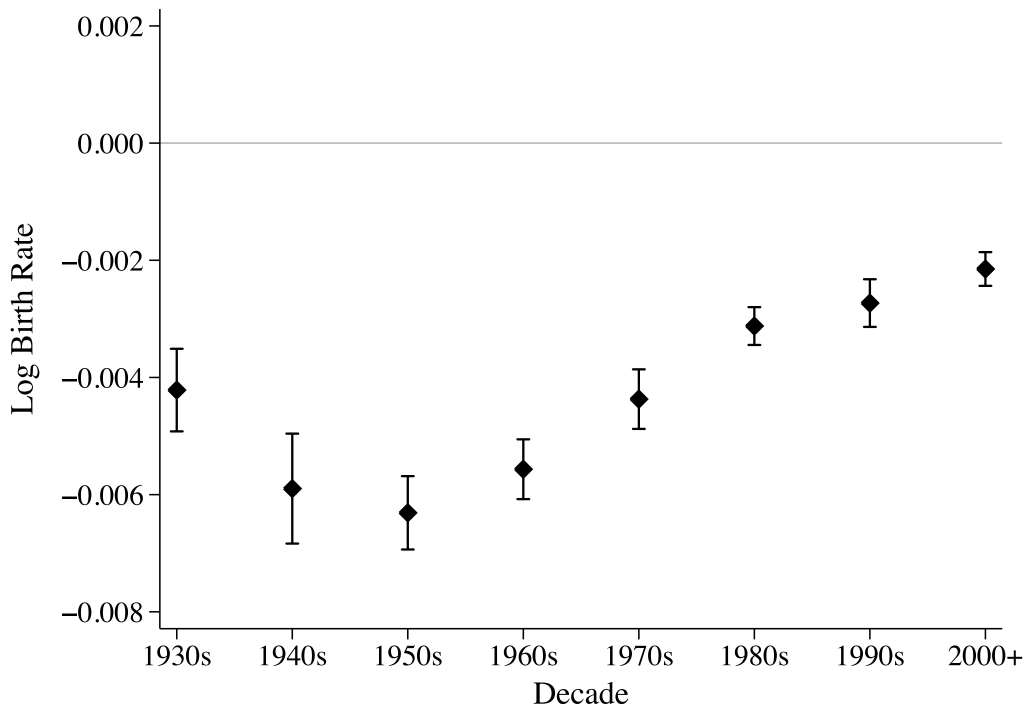


Panel B: Predictions, by census region



Note: See note to Figure 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+10 only" model only controls 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.

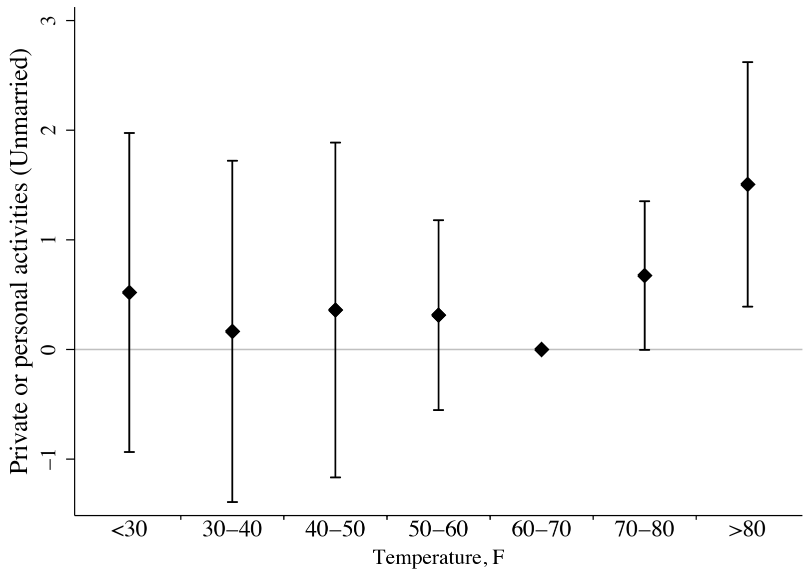
Figure 5: Estimated Temperature-Fertility Relationship: Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate 9 Months Later, by Decade



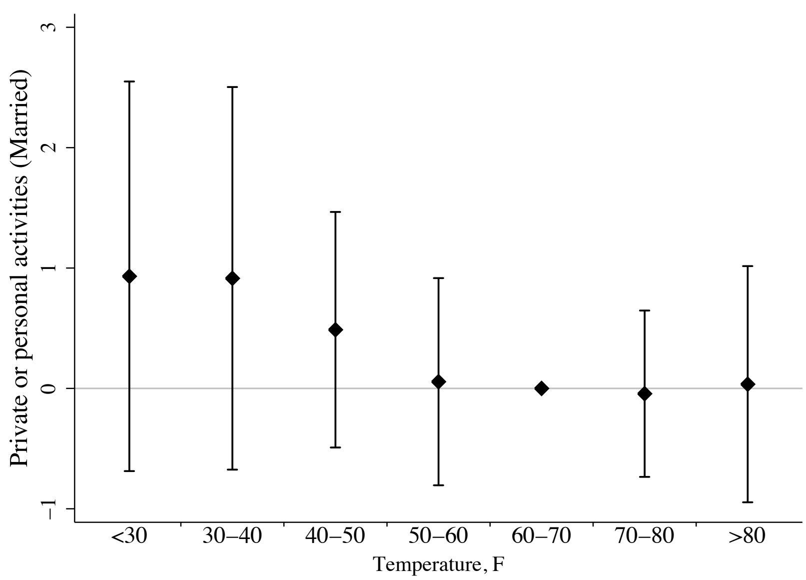
Note: The diamonds are the point estimates and the brackets represent +/- two standard errors. We restrict the exposure months 8-13. We use the full sample of years and interact the temperature variables with an indicator for the given decade. We include 2010 in the 2000s. See note to Figure 2 for details on the other model controls.

Figure 6: Estimated Temperature-Sex Relationship: Effect of Daily Mean Temperatures on Personal and Private Activities in ATUS data (2004-2010)

Panel A: Unmarried individuals, 18-45 years old



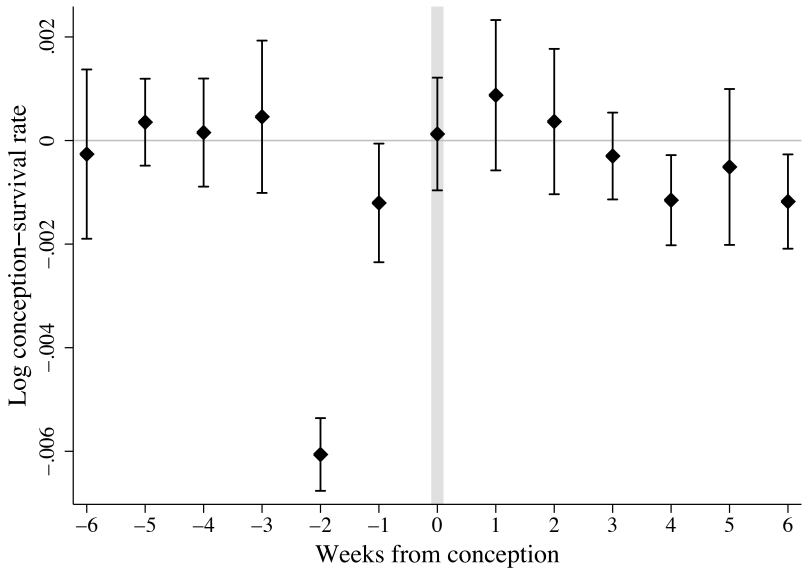
Panel B: Married individuals, 18-45 years old



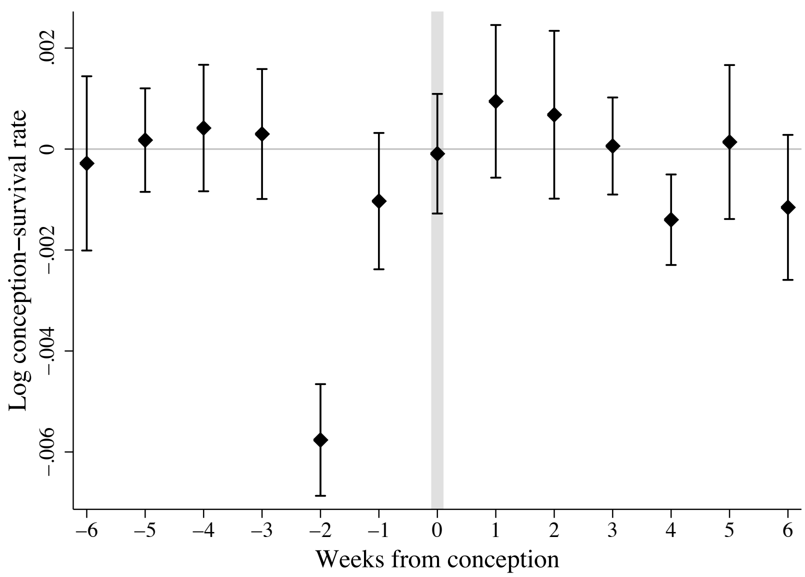
Note: The diamonds are the point estimates and the brackets represent two standard errors around the point estimates. Temperatures between 60 and 70 °F are the omitted category. The outcome data come from the American Time Use Survey for the years 2004 through 2010. The outcome is an indicator for any same-day "personal or private activities", which includes "cuddling partner in bed, having sex, making out, necking, personal activity (unspecified), private activity (unspecified), and spouse gave me a massage (2007+)". The sample is restricted to 18-45 year olds. The model includes state-by-month fixed effects, state-by-year fixed effects, and year-month-day fixed effects. The model also includes an indicator for precipitation levels between 0.01 and 0.50 inches, and greater than 0.51 inches. Regressions are weighted by the state population in the year of observation.

Figure 7: Estimated Impact Around the Time of Conception: Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Conception-Survival Rate

Panel A: All births



Panel B: Excluding births where the menses falls on the 1st, 5th, 10th, 15th, 20th, 25th, 28th, and 30th of the month.



Note: 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 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 (F) < 30	2.9	4.2	5.3	0.8	1.3
Mean temp (F) 30-40	3.4	4.9	4.6	2.2	2.1
Mean temp (F) 40-50	4.4	5.1	4.3	3.9	4.5
Mean temp (F) 50-60	5.6	5.2	4.7	5.1	8.5
Mean temp (F) 60-70	6.1	5.7	5.5	5.9	8.2
Mean temp (F) 70-80	5.8	4.7	5.1	7.9	4.2
Mean temp (F) > 80	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 on, while state of occurrence is only available 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 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
			Panel 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)*
			Panel 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)*
			Panel C: By time period				
1970-2010	-0.083	-0.316	-0.153	0.035	0.073	0.049	-0.394
	(0.018)*	(0.011)*	(0.011)*	(0.011)*	(0.010)*	(0.010)*	(0.033)*
1931-1969	0.008	-0.538	-0.300	0.138	0.153	0.052	-0.487
	(0.013)	(0.023)*	(0.024)*	(0.012)*	(0.019)*	(0.017)*	(0.045)*
Difference	-0.090	0.223	0.148	-0.103	-0.080	-0.004	0.093
	(0.019)*	(0.019)*	(0.023)*	(0.014)*	(0.014)*	(0.023)	(0.045)*

Notes: * significant at <5% level. The estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °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 over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) 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 are clustered at the state level. Here, we interact the temperature variables with an indicator for whether the state is a "hot state" (Panel B) or the year is 1970 or later (Panel C). Hot states are those states that have above the median number of >80 °F days over the sample period.

Table 3: Impact of Residential Air Conditioning on the Temperature-Fertility Relationship: Interaction Effect with Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
			Panel 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 x >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)
			Panel 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 x >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 x >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+ x >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)
HS degree x >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 x >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 x >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 x >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: * significant at <5% level. See notes to Figure A4 for a description of the basic model. Standard errors are in parentheses. These are the estimates from equation (1) with the temperature bins as main effects, but with the temperature variables interacted with the added variables, like air conditioning (Panel A). The regressions are weighted by state-year population in the preceding year. Standard errors are clustered at the state level. The sample period is 1931-2010.

See 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 between 18 and 45 with a high school diploma. We create an indicator equal to one 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 in 1970 and that all other states legalized in 1973. The "Pill 21+" variable controls for whether unmarried women under the age of 21 could legally obtain the birth control pill 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). 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.

Table 4: Differences in Temperature-Fertility Relationship by Day and Time of Exposure: The Effect of Temperature on Log Birth Rate (x 100), by Months from Exposure

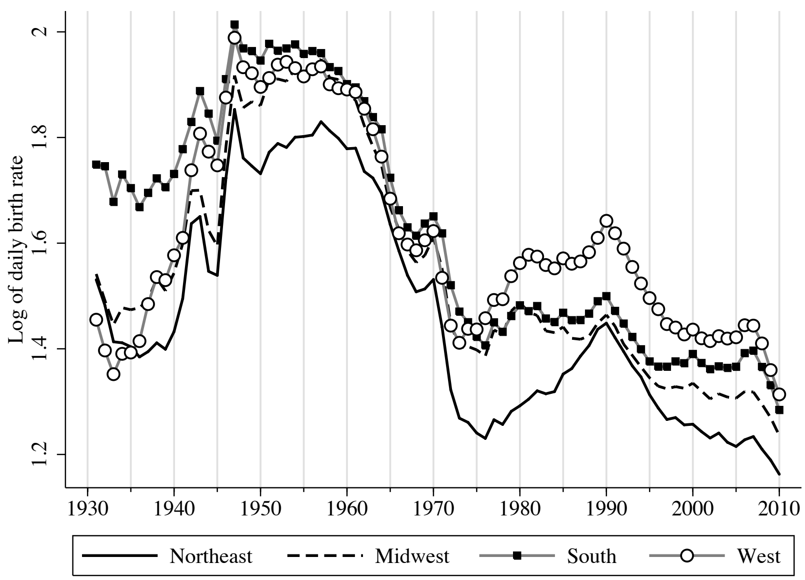
	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
			Panel A: By day of week				
Weekend x Days >80 °F	-0.044	-0.429	-0.185	0.073	0.099	0.094	-0.391
	(0.023)	(0.032)*	(0.026)*	(0.021)*	(0.026)*	(0.025)*	(0.098)*
Weekday x Days >80 °F	-0.065	-0.370	-0.227	0.061	0.098	0.018	-0.484
	(0.021)*	(0.021)*	(0.025)*	(0.020)*	(0.017)*	(0.020)	(0.075)*
Difference	0.021	-0.059	0.042	0.011	0.001	0.076	0.093
	(0.032)	(0.044)	(0.043)	(0.036)	(0.035)	(0.042)	(0.160)
			Panel B: Minimum vs. Maximum Temperature				
Days w/ min. > 70 °F	-0.058	-0.373	-0.226	0.032	0.064	0.024	-0.537
	(0.023)*	(0.030)*	(0.023)*	(0.016)*	(0.013)*	(0.014)	(0.077)*
Days w/ max > 90 °F	-0.006	-0.114	-0.038	0.035	0.043	0.034	-0.046
	(0.011)	(0.022)*	(0.013)*	(0.011)*	(0.014)*	(0.011)*	(0.051)
			F-statistic on full distribution of temperatures				
Minimum temperature	6.0	44.8	22.8	1.4	5.3	1.6	155.6
p-value	0.000	0.000	0.000	0.251	0.000	0.158	0.000
Maximum temperature	2.6	21.5	3.6	4.5	4.4	2.5	18.0
p-value	0.031	0.000	0.005	0.001	0.001	0.033	0.000

Notes: * significant at <5% level. The estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °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 over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) 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 are clustered at the state level. In Panel A, weekend days are defined as Friday, Saturday, and Sunday, while weekdays are Monday, Tuesday, Wednesday, and Thursday. In Panel B, the model includes minimum temperature bins <30, 30-40, 40-50, 50-60 (omitted), 60-70, and >70 along with maximum temperature bins <40, 40-50, 50-60, 60-70, 70-80 (omitted), 80-90, and >90 for all exposure months, though we only report the coefficient on minimum temperature >70 and maximum temperature >90 here.

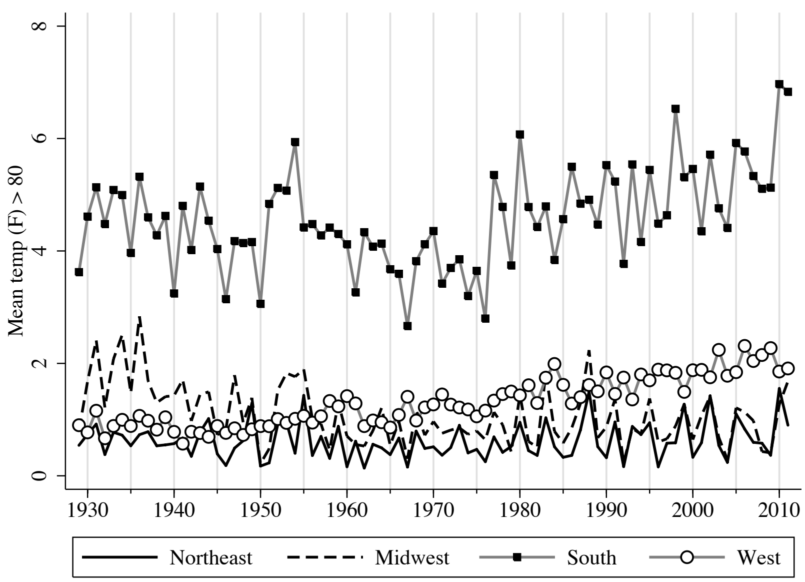
Appendix Section A: Robustness Checks and Supporting Exhibits For Online Publication

Figure A1: Annual Means of Log Birth Rates and Days >80 °F , by Census Region

Panel A: Log birth rates

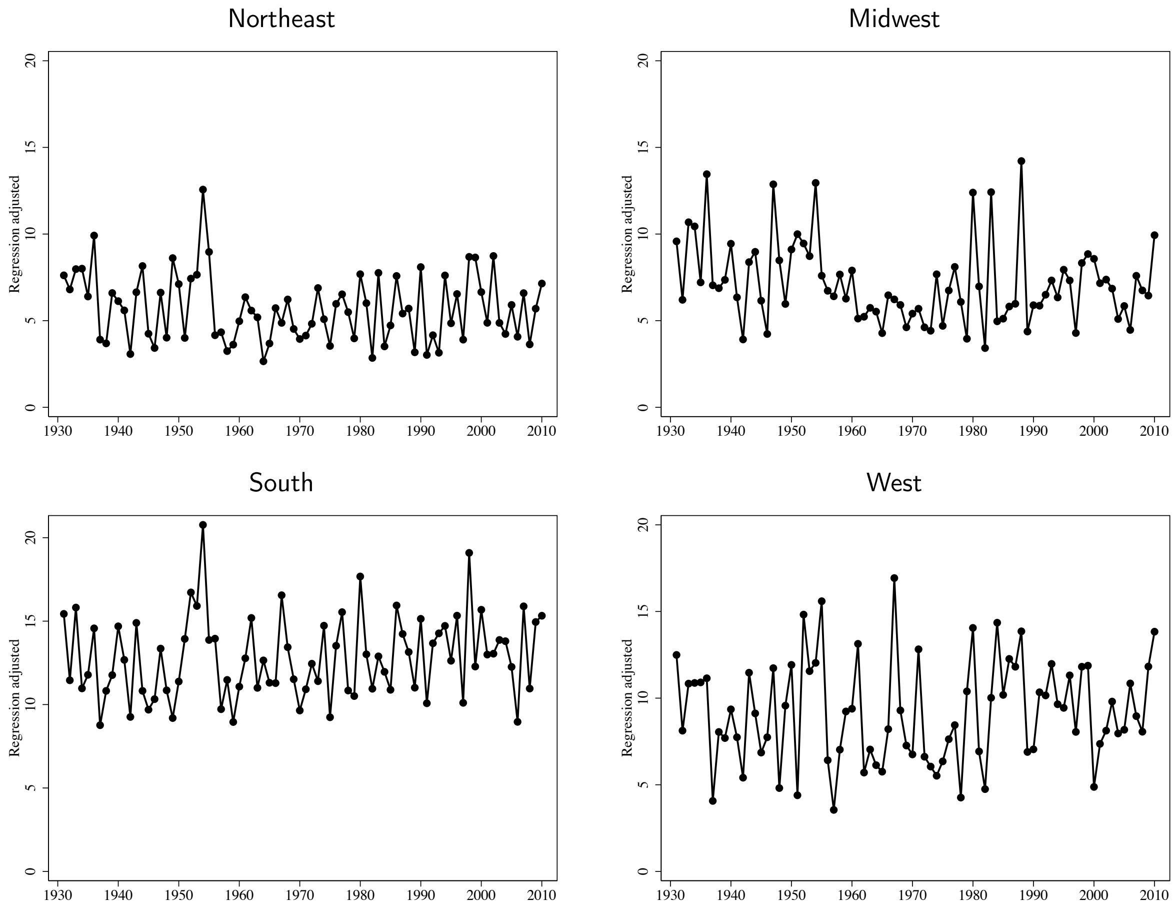


Panel B: Days > 80 °F per month



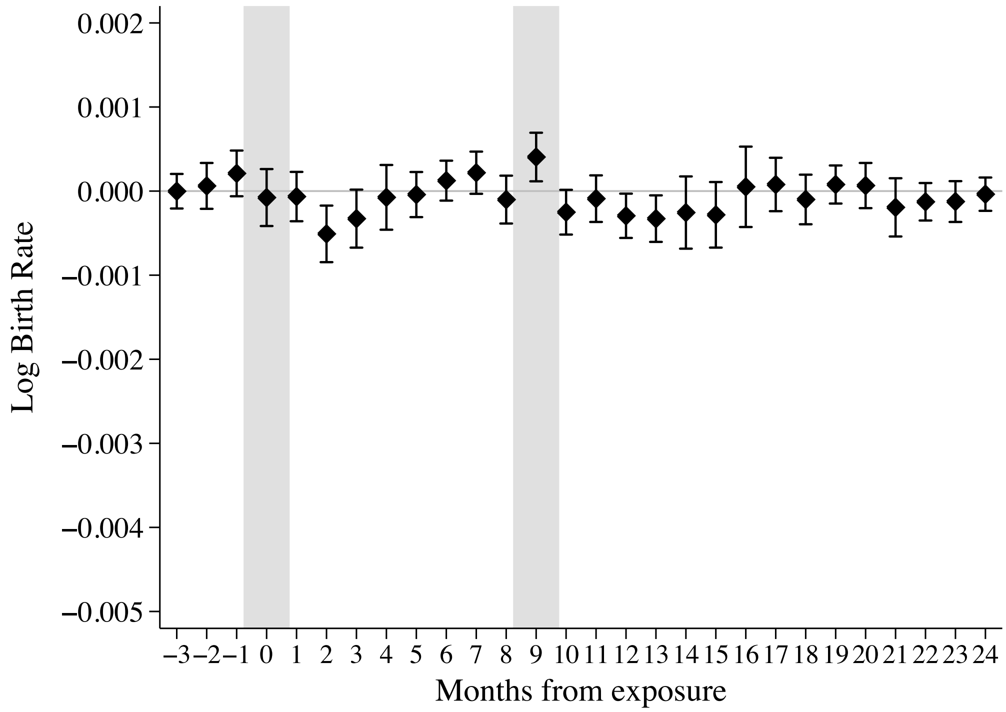
Note: Averages use state-year populations as weights.

Figure A2: Annual Deviations in Days >80 °F from Regression Adjusted Mean Predictions, by Census Region



Notes: This figure illustrates average annual deviations in days >80 °F from a regression that controls for our core set of fixed effects, which include year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar month quadratic time trends, and state-year fixed effects. The figures are the average annual deviations for each region, weighted by the state's population.

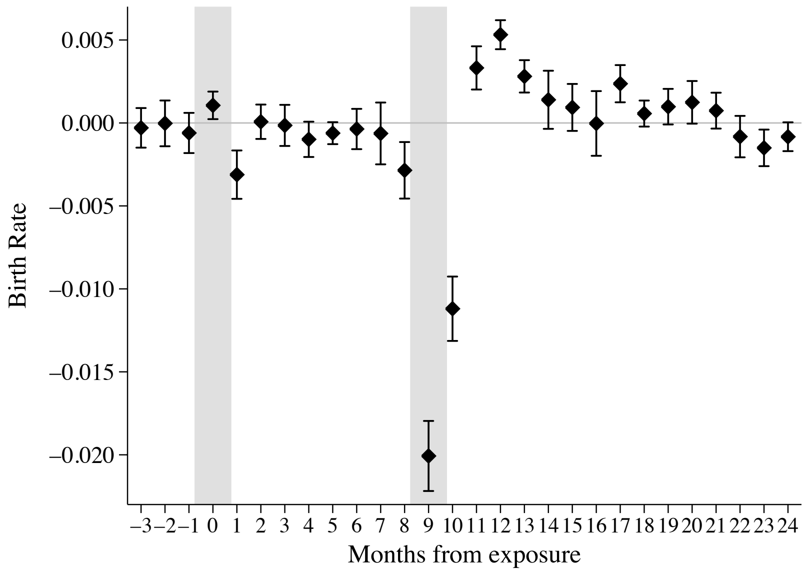
Figure A3: Estimated Temperature-Fertility Relationship: Effect of Daily Mean Temperature <30 °F Relative to 60-70 °F on Log Birth Rate, by Months from Exposure



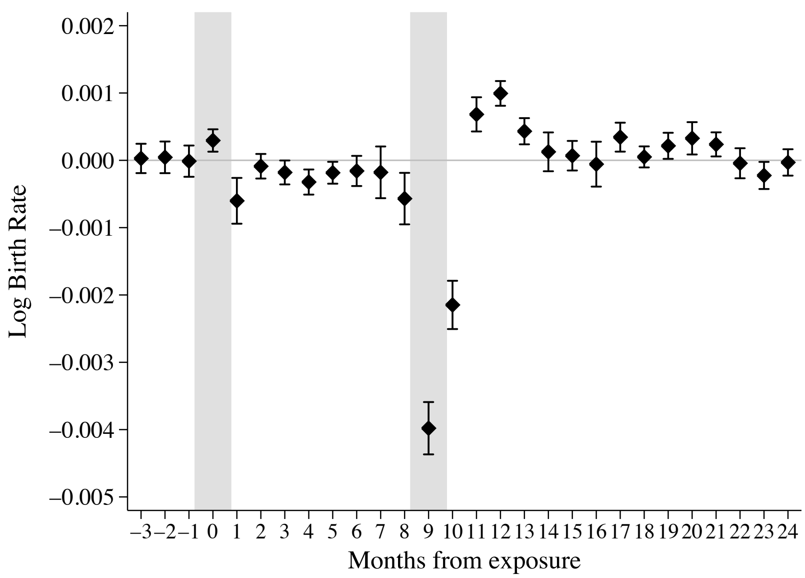
Note: See notes to Figure 2.

Figure A4: Estimated Temperature-Fertility Relationship: Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Various Outcomes, by Months from Exposure

Panel A: Outcome is daily birth rate in levels



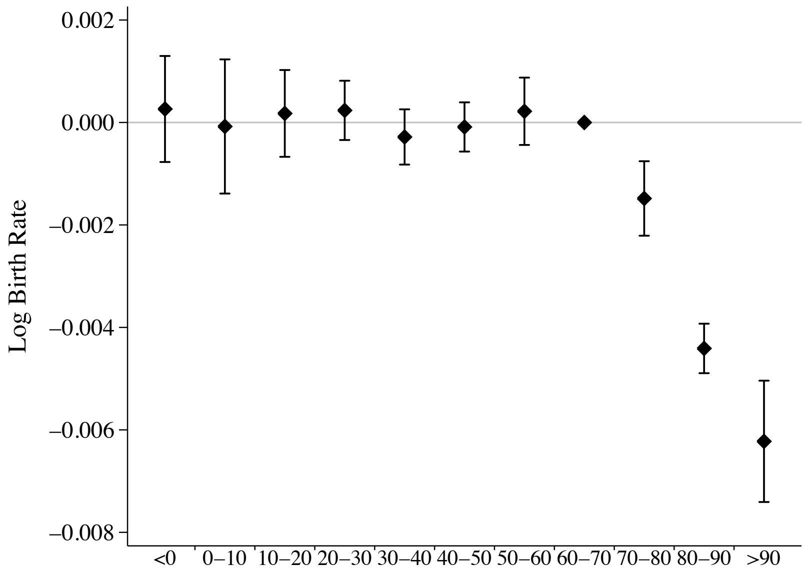
Panel B: Outcome is log of birth rate with female population 15-44 years old as denominator



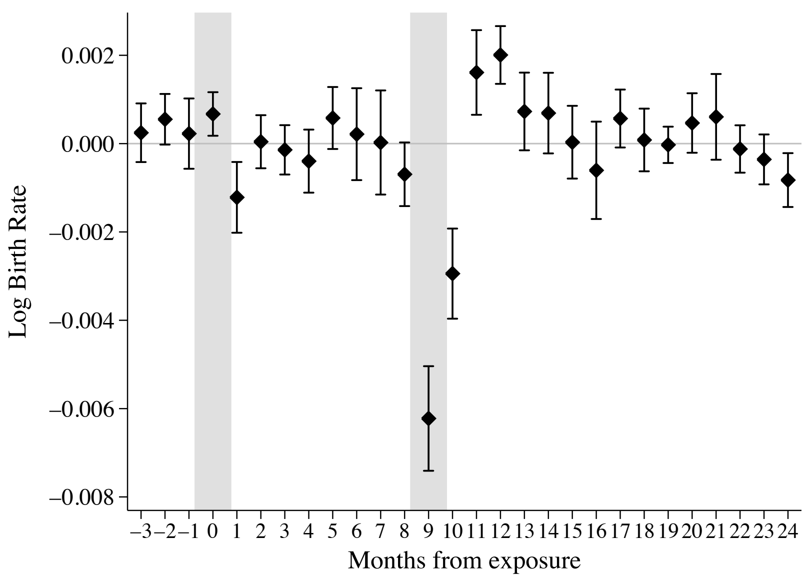
Note: See notes to Figure 2. The mean daily birth rate per 100,000 residents (population weighted) is 4.7.

Figure A5: Estimated Temperature-Fertility Relationship with Diurnal Temperature Bins

Panel A: Effect of 24 hours of diurnal temperatures on log birth rate 9 months later



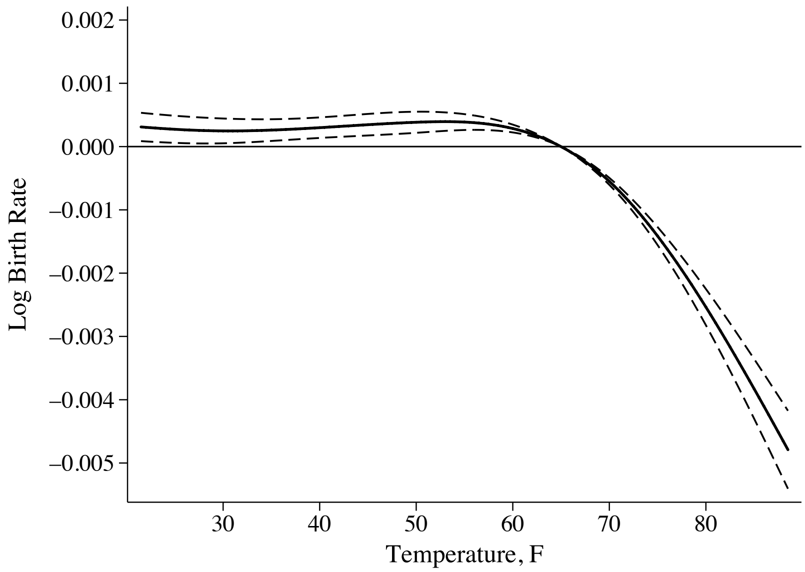
Panel B: Effect of 24 hours >90 °F relative to 60-70 °F on log birth rate, by exposure month



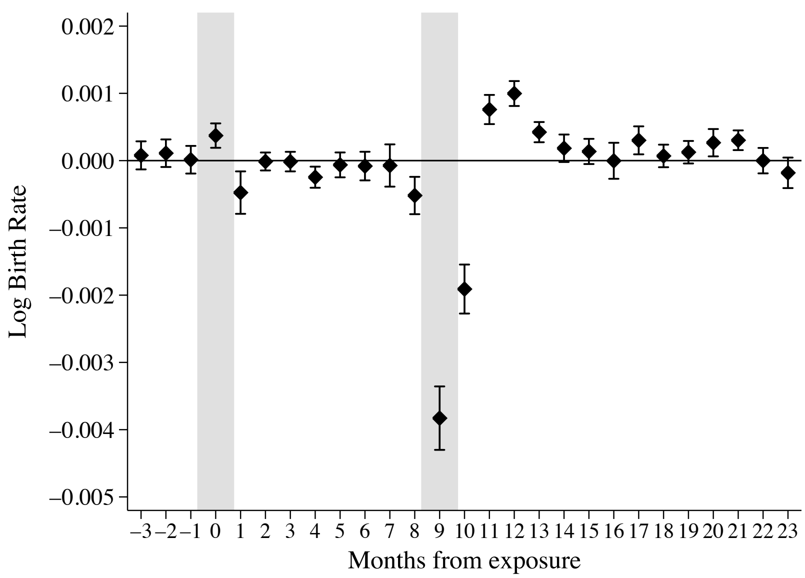
Note: See notes to Figure 2 for model controls. The estimates explore the effects of the proportion of the day in a 10 °F interval, where diurnal temperatures are linearly interpolated from the daily maximum and daily minimum temperature. The bounds are set at 0 F and 90 F.

Figure A6: Estimated Temperature-Fertility Relationship with Temperature Spline Model

Panel A: Effect of daily mean temperatures on log birth rate 9 months later



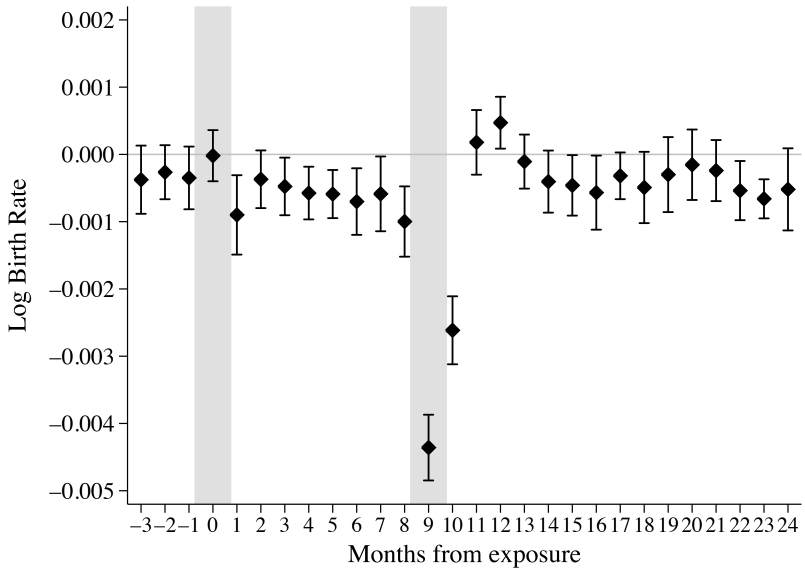
Panel B: Effect of daily mean temperature of 85 °F relative to 65 °F on log birth rate , by exposure month



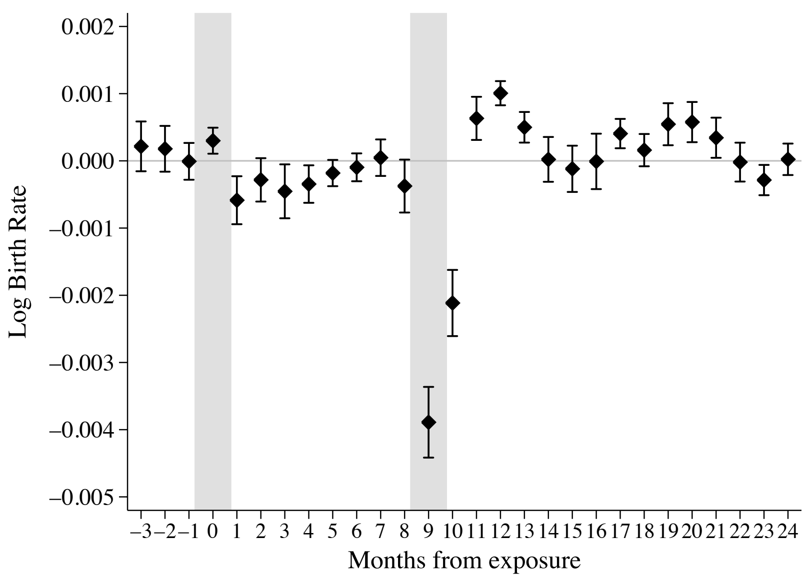
Note: See notes to Figure 2 for model controls. However, temperature is modeled as a cubic polynomial spline function with knots at daily mean temperatures of 10, 30, 40, 70, and 90 °F .

Figure A7: Different controls: Effect of daily mean temperature >80 °F relative to 60-70 °F on log birth rate , by exposure month

Panel A: Excluding state-by-year fixed effects



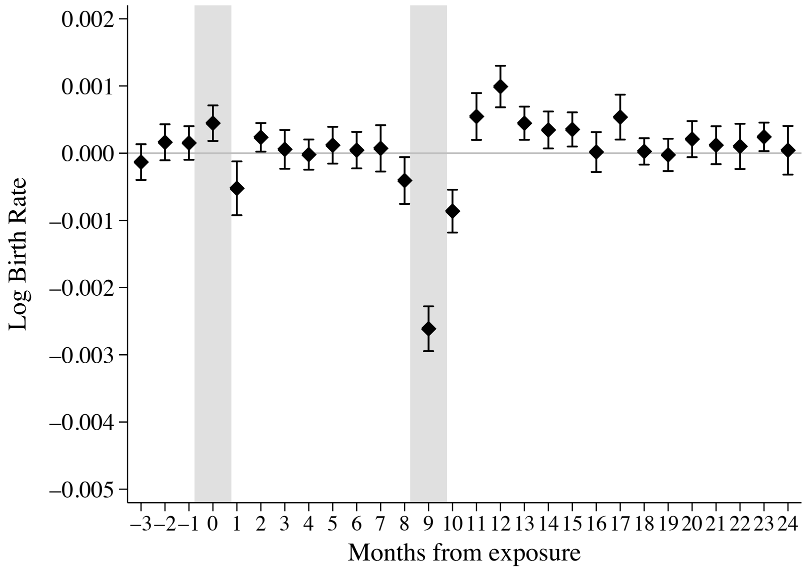
Panel B: Excluding state-by-calendar-month quadratic trends



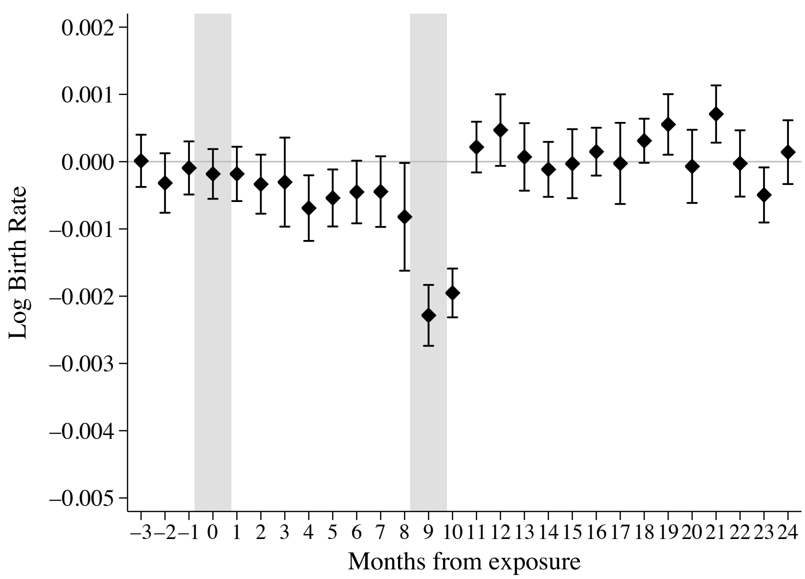
Note: See notes to Figure 2 on the temperature and precipitation controls. Panel A has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-calendar month quadratic time trends, but no state-by-year fixed effects. Panel B has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-year fixed effects, but no state-by-calendar month quadratic time trends.

Figure A8: Estimated Temperature-Fertility Relationship With Controls for Humidity, By Exposure Month

Panel A: Effect of daily mean temperature >80 °F relative to 60-70 °F on log birth rate



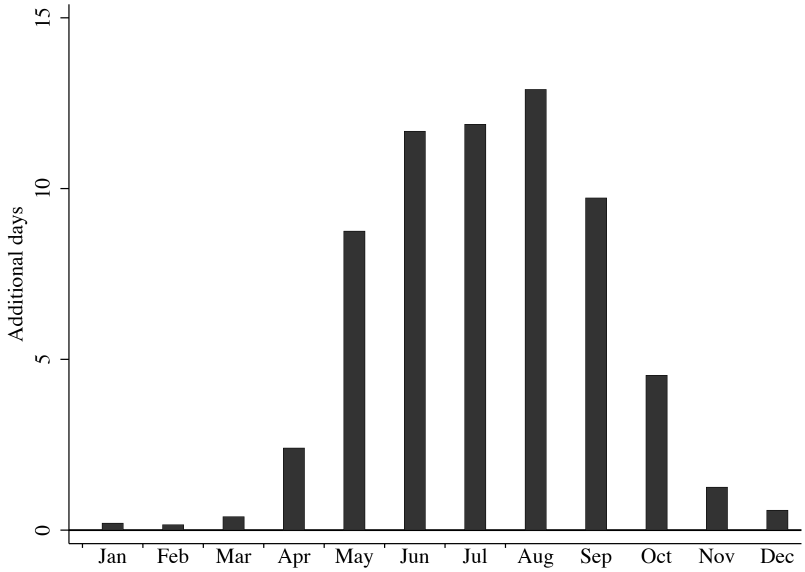
Panel B: Effect of daily mean specific humidity >18 g/kg relative to to 8-10 g/kg on log birth rate



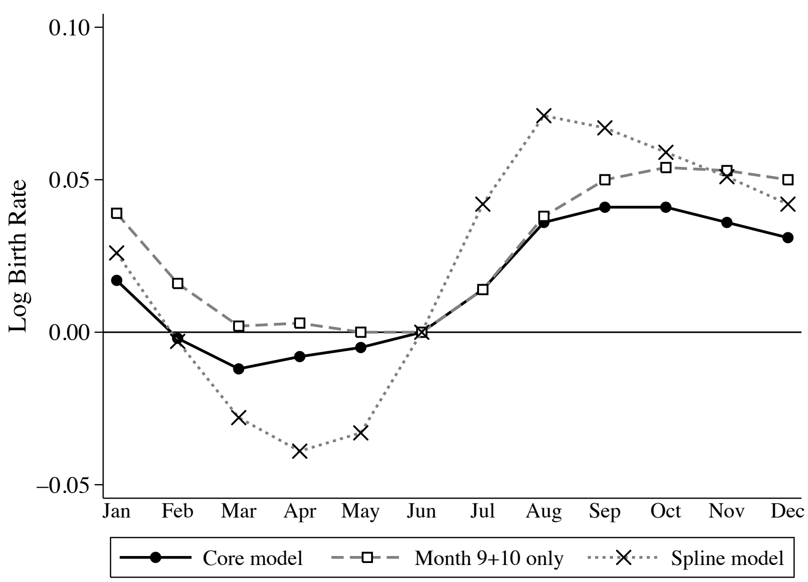
Note: See Figure 2 for model controls. Humidity is measured in terms of water vapor per kilogram of air (g/kg), Humidity is modeled in 2 g/kg bins with >18 grams as the upper category and 8-10 grams as the omitted category. Due to data limitations with the humidity variable, the sample is restricted to the 1945-2010 period. Humidity levels were >18 g/kg approximately 3 days per year in our sample.

Figure A9: Projected Changes in by 2070-2099, According to Error-Corrected Hadley CM3 A1FI

Panel A: Change in daily mean temperature >80 °F , by calendar month

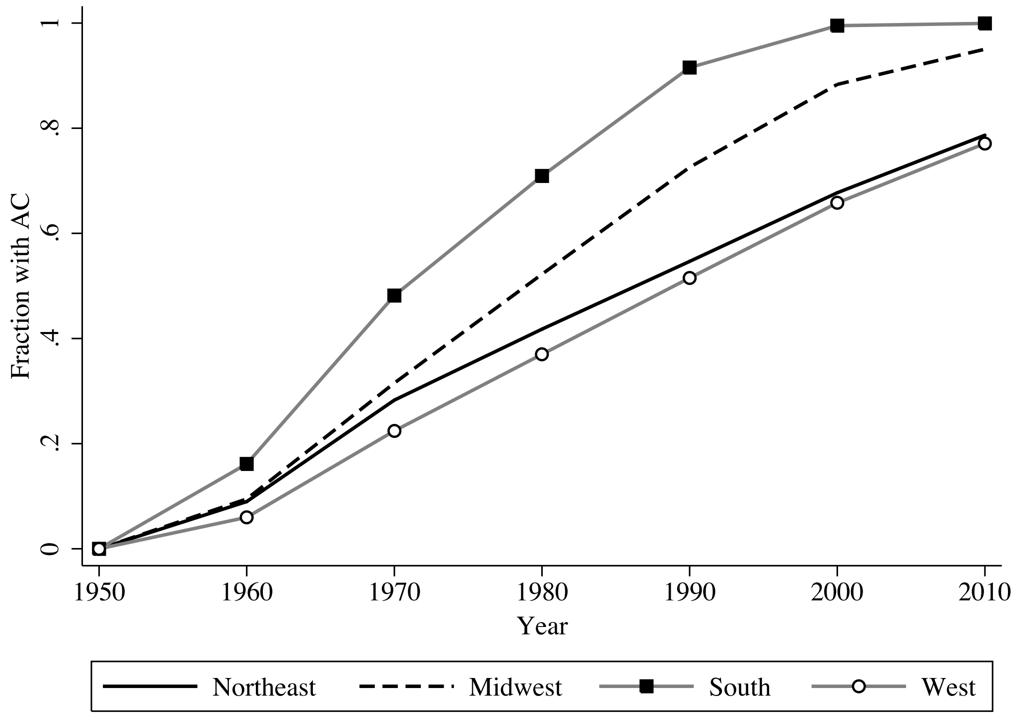


Panel B: Change in log birth rates, by calendar month



Note: Average exposures estimated using county population estimates in 2000 as weights. The climate change projections are "error corrected" to factor out the difference between the realized temperatures and model predictions for the 1990-2002 time period. The "Core model" projects changes in birth rates using the post-1970 temperature estimates from Table A4 Panel B. The "Months 9+10 only" model only controls for exposure in months 9 and 10. The "Spline model" controls for temperature as a cubic polynomial spline with knots at 10, 30, 50, 70, and 90 °F across the same exposure months as the "Core model".

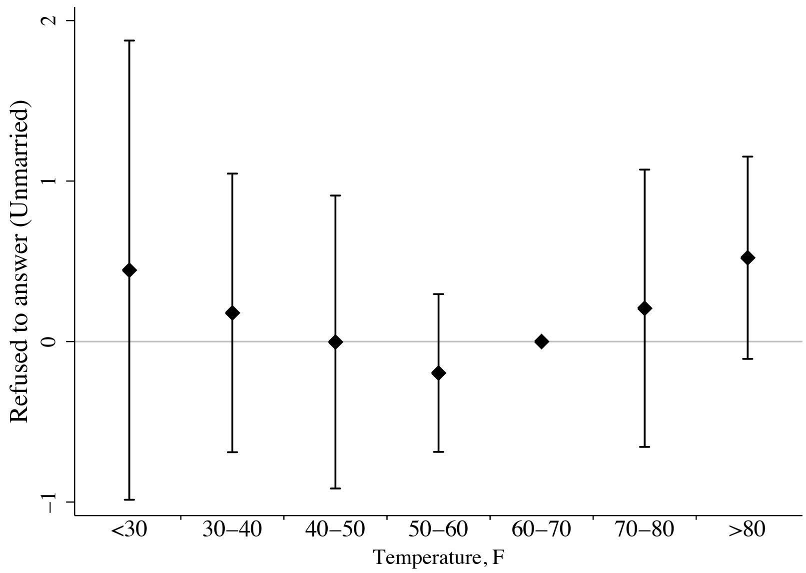
Figure A10: Residential Population with Air Conditioning



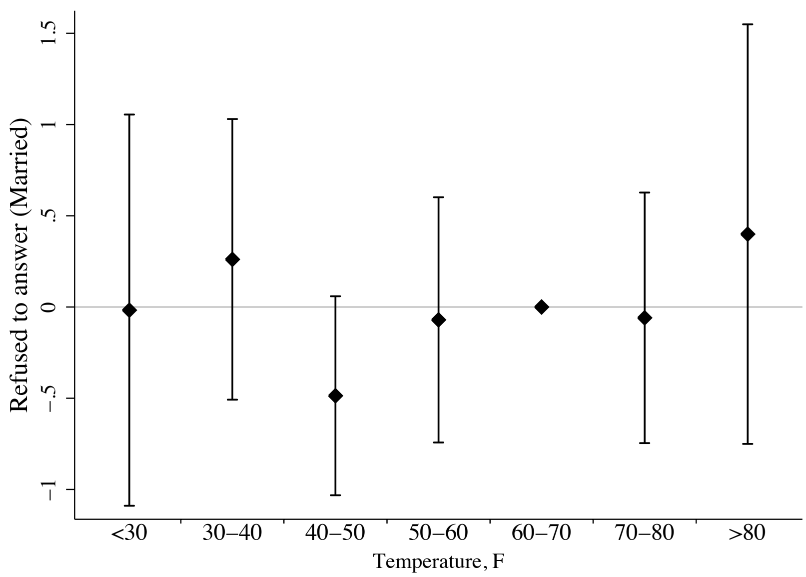
Note: Air conditioning coverage is the fraction of the population in the respective Decennial Census that had at least one air conditioning unit or central air conditioning. The calculations linearly interpolate coverage using the 1960, 1970, and 1980 Census and assuming no coverage as of 1950.

Figure A11: Estimated Temperature-Sex Relationship: Effect of Daily Mean Temperatures on "Refuse to respond" in ATUS data (2004-2010)

Panel A: Unmarried individuals, 18-45 years old



Panel B: Married individuals, 18-45 years old



Note: See Figure 6 note. The outcome is "refused to answer", which includes responses like "none of your business".

Table A1: Theoretical Relationship Between Adverse Temperature Shocks and Monthly Birth Rates

	Months after temperature shock																								
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Scenario A																									
Constant conception probability after month 0										$\downarrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$
Secnario B																									
Constrained to conceiving in one calendar month										$\downarrow$												$\uparrow$			
Scenario C																									
1-month reduction in gestational length	$\uparrow$	$\downarrow$																							
Scenario D																									
Fetal loss after 1 month of gestation with immediate recovery									$\downarrow$		$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$	$\uparrow$

Notes: The temperature shock occurs in month 0. In the scenarios above, we assume: a 9-month gestational length, menstrual cycles last one calendar month, and the population does not become susceptible to pregnancy again after a live birth. For Scenario A, we assume constant conception probabilities after month 0. For Scenario C, we assume exposure occurs in the 8th month of gestation. For Scenario D, we assume the population becomes susceptible again in the month immediately following the fetal losses.

Table A2: The Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Infant Health and Mother Characteristics, by Months from Exposure

	Months after temperature shock					
Outcome:	8	9	10	11	12	13
Infant health						
Female birth (x100)	0.007	0.000	-0.004	0.005	-0.001	0.001
Mean = 48.8	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)
Birthweight	0.261	-0.126	-0.508	-0.087	0.055	0.068
Mean = 3320.7	(0.070)*	(0.082)	(0.073)*	(0.061)	(0.085)	(0.060)
Low birth weight (<2500 grams) (x 100)	-0.010	0.011	0.017	0.000	-0.002	0.001
Mean = 7.5	(0.002)*	(0.003)*	(0.002)*	(0.003)	(0.003)	(0.002)
Overdue delivery (>41 weeks) (x100)	-0.001	0.013	-0.014	-0.005	-0.007	0.000
Mean = 10.3	(0.005)	(0.004)*	(0.004)*	(0.005)	(0.005)	(0.003)
Pre-term delivery (<37 weeks) (x100)	-0.015	0.009	0.023	0.002	0.000	0.000
Mean = 10.9	(0.004)*	(0.004)*	(0.005)*	(0.004)	(0.004)	(0.004)
Maternal characteristics						
Mother is non-white (x100)	-0.003	-0.025	-0.006	0.009	0.010	0.013
Mean = 18.3	(0.004)	(0.007)*	(0.004)	(0.005)	(0.005)*	(0.005)*
Mother's age is <=19 (x100)	-0.005	-0.005	-0.004	-0.002	0.000	-0.003
Mean = 14.0	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)
Mother's age is >=35 (x100)	0.002	-0.004	-0.005	-0.005	-0.002	0.000
Mean = 8.7	(0.002)	(0.002)	(0.002)*	(0.002)*	(0.003)	(0.003)
Mother has less than HS (x100)	-0.010	-0.023	0.000	0.004	0.003	0.007
Mean = 23.3	(0.006)	(0.004)*	(0.006)	(0.007)	(0.004)	(0.005)
Father's age missing (x100)	-0.001	-0.013	-0.003	0.006	-0.003	0.007
Mean = 13.5	(0.005)	(0.005)*	(0.004)	(0.006)	(0.006)	(0.005)

Notes: See notes to Table A4. Estimates are weighted by the number of births.

Table A3: Heat Waves and the Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
			Panel A: Core model				
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)*
			Panel B: Heat wave = 3 consecutive days >80 °F				
Days >80 °F	-0.048	-0.359	-0.240	0.058	0.092	0.050	-0.447
	(0.024)*	(0.029)*	(0.021)*	(0.024)*	(0.024)*	(0.018)*	(0.086)*
Heat wave	-0.009	-0.049	0.042	0.009	0.007	0.000	0.000
	(0.035)	(0.027)	(0.023)	(0.026)	(0.025)	(0.019)	(0.090)
			Panel C: Heat wave = 5 consecutive days >80 °F				
Days >80 °F	-0.050	-0.373	-0.227	0.058	0.098	0.049	-0.446
	(0.017)*	(0.021)*	(0.016)*	(0.016)*	(0.017)*	(0.012)*	(0.056)*
Heat wave	-0.007	-0.041	0.033	0.010	0.000	0.002	-0.003
	(0.027)	(0.020)*	(0.017)	(0.018)	(0.017)	(0.014)	(0.062)

Notes: * significant at <5% level. Panel B and Panel C add a control for whether the day is the third or fifth consecutive day >80 °F . The "Days >°F " estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °F when fewer than 2 or 4 of the previous days were >80 °F . The "Heat Wave" estimate captures the added effect of one >80 °F day when 2+ or 4+ of the previous days were >80 °F . The The model controls for exposure months 8-13. We control for fraction of days with precipitation between 0.01 and 0.50 inches and over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) 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 are clustered at the state level.

Table A4: Single-Month Models and the Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock					
	8	9	10	11	12	13
			Panel A: Core model			
Months 8-13	-0.055	-0.396	-0.209	0.066	0.098	0.049
	(0.015)*	(0.016)*	(0.014)*	(0.009)*	(0.012)*	(0.007)*
			Panel B: Various models controlling for one month at a time			
Month 8 only	-0.087					
	(0.018)*					
Month 9 only		-0.428				
		(0.016)*				
Month 10 only			-0.234			
			(0.015)*			
Month 11 only				0.094		
				(0.010)*		
Month 12 only					0.174	
					(0.017)*	
Month 13 only						0.128
						(0.010)*

Notes: * significant at <5% level. The estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °F . The Panel A model controls for exposure months 8-13 simultaneously, while Panel B includes several models with only one exposure month. We control for fraction of days with precipitation between 0.01 and 0.50 inches and over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) 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 are clustered at the state level.

Table A5: Maternal Age and the Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
Ages 15-19	-0.101	-0.342	-0.173	0.041	0.065	0.013	-0.498
	(0.031)*	(0.026)*	(0.026)*	(0.042)	(0.030)*	(0.027)	(0.080)*
Ages 20-24	-0.069	-0.306	-0.111	0.066	0.079	0.039	-0.302
	(0.025)*	(0.023)*	(0.021)*	(0.020)*	(0.015)*	(0.017)*	(0.061)*
Ages 25-29	-0.076	-0.316	-0.145	0.051	0.071	0.037	-0.378
	(0.024)*	(0.028)*	(0.023)*	(0.021)*	(0.015)*	(0.020)	(0.065)*
Ages 30-34	-0.012	-0.327	-0.163	0.062	0.073	0.078	-0.288
	(0.023)	(0.024)*	(0.026)*	(0.036)	(0.020)*	(0.025)*	(0.082)*
Ages 35-39	-0.071	-0.434	-0.231	0.034	0.044	0.026	-0.632
	(0.045)	(0.049)*	(0.038)*	(0.033)	(0.038)	(0.049)	(0.125)*
Ages 40-44	-0.100	-0.423	-0.306	-0.203	-0.035	0.045	-1.022
	(0.118)	(0.086)*	(0.100)*	(0.092)*	(0.073)	(0.080)	(0.240)*

Notes: * significant at <5% level. The birth rate is calculated using the total number of births divided by the estimated population for that age group. The sample spans the years of the detailed Natality Data, i.e. 1968-2004. The estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °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 over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) 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 are clustered at the state level.

Table A6: Metropolitan Status of County and the Effect of Daily Mean Temperature >80 °F Relative to 60-70 °F on Log Birth Rate (x 100), by Months from Exposure

	Months after temperature shock						Cumulative
	8	9	10	11	12	13	8-13
Days >80 °F	-0.135	-0.434	-0.216	0.106	0.100	0.091	-0.488
	(0.046)*	(0.039)*	(0.038)*	(0.032)*	(0.038)*	(0.034)*	(0.145)*
Metro x >80 °F	0.078	0.088	0.076	-0.035	0.000	-0.029	0.178
	(0.046)	(0.044)*	(0.044)	(0.037)	(0.044)	(0.042)	(0.175)

Notes: * significant at <5% level. The unit of observation is at the state-year-month-metro status level. We first match births and weather in a given county-year-month. In order to address zero births in smaller counties and reduce computing costs, we then collapse the data to the state-year-month-metro status level, where the metro status is an indicator for whether the county was designated as metropolitan in 1988. The birth rate is calculated using the total number of births divided by the estimated population in the metropolitan areas in that state-year. The sample spans the years of the detailed Natality Data with publicly available county identifiers, i.e. 1968-1988. We use the Natality Data's designation of metropolitan status. The main estimates can be interpreted as the impact on the log monthly birth rate (x100) of one additional day with a mean temperature >80 °F relative to 60-70 °F in non-metro counties, while the interaction gives the marginal effect of being in a metro county. The model controls for exposure months 8-13. We control for fraction of days with precipitation between 0.01 and 0.50 inches and over 0.51 inches in each month as well as the effects in other temperature bins (i.e. <30, 30-40, 40-50, 50-60, 70-80 °F) in each month. The controls include year-month fixed effects as main effects and interacted with metro status; state-by-calendar-month fixed effects as a main effect and interacted with metro status; state-by-calendar month quadratic time trends, and state-year fixed effects. Estimates are weighted by state-year-metro status population. Standard errors are clustered at the state level.