Maybe Next Month? The Dynamic Effects of Ambient Temperature on Fertility

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February 2015

Abstract

We investigate how high-frequency variation in climatic conditions affects fertility outcomes. Specifically, we estimate the effects of ambient temperatures on state-by-month birth rates and infant health in the United States (c. 1931-2010). Unusual shifts in the distribution of daily mean temperatures for a given state and calendar month provide the identifying variation. Consistent with other research, we find high temperatures cause a decline in birth rates approximately 8 to 10 months later. However, we present novel evidence the initial decline is followed by an increase in births over the next few months (11, 12, and 13 months after exposure). Importantly, this temporal shift has a hidden cost in terms of worse health outcomes. Exposure to hot days in the third trimester leads to lower birth weight and higher rates of preterm delivery, and shifting conceptions from summer months to winter months exposes more children to summer heat during the critical third trimester the following year. Also, we investigate how the temperature-fertility relationship has changed over time, and consider the implications of our findings in the context of climate change.

JEL codes: J13, I12

Keywords: Fertility, birth rates, seasonality, birth weight, temperature, climate change

*The authors thank the numerous seminar participants at the IZA Conference on the Labor Market Effects of Environmental Policies, Oberlin College, Tulane University, University of Houston, and University of Mississippi, and 2014 Southern Economic Association Meetings. In addition, thanks are deserved to D. Mark Anderson, Daniel Hungerman, and Nick Sanders. Barreca (corresponding author) can be contacted via email at abarreca@tulane.edu, Deschenes at olivier@econ.ucsb.edu, and Guldi at 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. When we reflect on this struggle, we may console ourselves with the full belief, that the war of nature is not incessant, that no fear is felt, that death is generally prompt, and that the vigorous, the healthy, and the happy survive and multiply.

— Charles Darwin, *On The Origin of Species* (1859)

Charles Darwin posited seasonal changes in environmental conditions play an important role in population growth and evolution of population health. While Darwin’s hypothesis still seems applicable to humans in modern times, the relative significance of any particular seasonal factor is not so transparent. We focus on the relationship between ambient temperature and human fertility, where the effect is plausibly operating through impacts on reproductive health and/or coital frequency. Our model estimates the effects of ambient temperature on state-month birth rates and infant health in the United States over an 80-year period (c. 1931–2010). Estimating the temperature-fertility relationship is of policy interest for two key reasons. First, these estimates help determine whether projected climatic changes in the coming century will meaningfully impact population growth. Second, the estimates help establish whether climatic factors explain observed differences in birth rates and infant health across season of the year.

The strong seasonality in births throughout the world provides suggestive evidence ambient temperature has an economically meaningful impact on fertility. Figure 1 plots the seasonal relationship in birth rates for the United States, Germany, and Australia for the years 2000 through 2010. In the United States and Germany, births peak in the hot summer months, circa August. In Australia, births have two peaks: the winter month of August, and a secondary peak in the summer month of March. This consistent spike in summer births across hemispheres suggests temperature is an important factor. However, confounders that vary seasonally (e.g.
nutrition) hinder causal inference with regards to temperature.\(^1\) And, even abstracting from those confounders, the seasonal relationship could reflect the causal effect of temperature on medium-term cumulative birth rates or simply a short-term shift in timing across months.

Few studies quantify the temperature-fertility relationship using observational data (Siever 1985, 1989; Lam and Miron 1991b, 1996; Lam, Miron and Riley, 1994). Most notably, Lam and Miron (1996) (hereafter LM) was the first study to rigorously examine the impact of temperature on birth rates in the United States, using state-by-month birth data from 1942 through 1988. To address potential seasonal confounders, LM focus on estimating the effects of monthly mean temperature on aseasonal birth rates by state. They find extreme heat reduces birth rates 9 to 10 months later, but find no evidence of a shift in births to subsequent months.

We also analyze the temperature-fertility relationship using state-by-month data, but across the longer period of 1931 through 2010. These data represent the longest panel of monthly birth rates for the United States (to our knowledge). The identifying variation in our empirical model comes from unusual variation in temperature. Specifically, we include state-by-calendar month fixed effects so plausibly unexpected changes in temperature, for a given state and month, identify our estimates. As such, our research credibly evaluates the causal impact of actual conditions around the time of conception, but abstracts from how expectations might influence fertility decisions. In this regard, our work is similar to LM.

Our empirical model adds two innovative features to the existing literature. First, we allow for more flexibility in the temperature-fertility response function. Our core specification models the effects of daily temperatures using a smoothed spline function with several “knots” (or potential kink points). Existing models impose much stricter functional form assumptions on the temperature-fertility relationship. For example, LM uses a quadratic in monthly average temperature. By exploring non-linear impacts at the day level, our approach offers more insight into the potential impacts of climate change, which likely includes a significant increase in climate change, which likely includes a significant increase in

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\(^1\) Other common hypothesized causes of seasonality include sunlight, holidays, availability of nutrition, and misinformed reproductive hypothesis (Bronson, 2009; Ellison, Valeggia, and Sherry, 2005; Lam and Miron, 1991a, Meade and Earicks, 2000; Rodgers and Udry, 1988; and Trovado and Odynak, 1993).

\(^2\) For example, a 1 °F increase in temperature may have a larger impact on fertility rates at 70 °F than at 90 °F.
extremely high-temperature days.² In the United States, for example, the Hadley CM3 “business as usual” climate model projects 40 additional days per year with mean daily temperatures above 90 °F (32 °C), compared to the current baseline of around 1 day per year.

Second, we comprehensively test for dynamic responses by allowing temperature to affect birth rates up to 18 months after exposure.³ For example, extreme temperatures may reduce fecundity and cause individuals to postpone coitus until the weather improves, which might manifest as an increase in births 12 months later. Accounting for this dynamic response provides a more accurate assessment of the cumulative impact of climatic changes on population growth. In addition, the model accounts for the possibility that extreme heat leads to an increase in fetal losses or causes forward displacement of births via reduced gestational lengths.

Our evidence indicates extreme heat leads to a sizable fall in births, followed by a modest rebound in births. Specifically, extremely hot days reduce birth rates 9-10 months after exposure, but increase births 11-13 months after exposure. For example, we find one additional day at 95 °F (35 °C), relative to one day at 65 °F (18 °C), reduces the birth rate 9 months later by 0.7% and increases the birth rate 10 months later by 0.4%. Then, birth rates increase by about 0.1% over each of the next few months (i.e. months 11, 12, and 13). Extremely cold temperatures lead to an economically small increase in births 9 months after exposure, but only in the latter half of our sample period. We also find evidence temperatures reduce gestational lengths, since we observe a forward displacement in births in the month of exposure. Our preferred model can explain approximately half of the seasonality in births in the United States.

The largest effects are observed at 9 months, which suggests temperature has a contemporaneous effect on conception probabilities. However, given the available data, we cannot definitely test the mechanisms through which temperature might reduce birth rates. For example, temperature extremes could affect coital frequency by changing mixing rates between potential mates.

² For example, a 1 °F increase in temperature may have a larger impact on fertility rates at 70 °F than at 90 °F. Previous studies have found non-linear relationships between temperature and mortality (Deschenes and Greenstone 2011; Barreca 2012). Given health could influence fertility patterns, allowing for non-linear effects is likely to be important.
³ Lam and Miron (1996) focus on months 9 and 10, though they footnote finding insignificant results in months 7, 8, and 11.
Alternatively, high temperatures may adversely affect reproductive health on either the male side, e.g. semen quality, or the female side, e.g. ovulation. However, we observe sizable effects at all maternal ages, suggesting that we can rule out risky behavior among the young as the main mechanism.

The shift in birth months has hidden costs for infant health outcomes since more children are born in the summer, increasing the risk of exposure to extreme heat in the third trimester. Consistent with Deschenes et al. (2009), we show exposure to extreme heat in the third trimester leads to a statistically significant increase in low birth weight and preterm deliveries. Thus, while the temporal shift helps mitigate impacts on cumulative birth rates in the medium term, more children will be exposed to extremely high temperatures during the critical third trimester. Our estimates also contribute to the debate concerning the impact of season of birth on infant health (e.g. Currie and Schwandt 2013). The extent to which early-life exposure to extreme heat has long-term consequences for health and economic outcomes is a pressing question for future research.\(^4\)

Two added components of our study have particular relevance to climate-change policy. First, we assess how vulnerability to extreme temperature has changed over time. Specifically, we estimate the temperature-fertility relationship at 10-year intervals from 1931 through 2010. We find a significant reduction in the response to extreme heat beginning in the 1970s. Additional analysis suggests access to air conditioning can explain about half of this dampening.

Second, we project effects into the coming century holding the temperature-fertility relationship constant. This projection ignores the possibility people adjust expectations about the frequency of future climatic shocks and make adaptive investments accordingly (Dell et al. 2014) and our model only captures shifts in births that occur in the medium-term (i.e. within 18 months). These limitations would lead us to overestimate impacts on cumulative birth rates. Nonetheless, our back-of-the-envelope calculation suggests a 3% decline in births by 2070-2099, with a more sizable 5% decline in the southern United States. This projection indicates climate change will

\(^4\) Almond and Currie (2011) survey the fetal-origins literature, which provides compelling evidence that early-life health shocks have consequences for lifelong outcomes.
exacerbate the already “below-replacement” birth rates in the United States, which is a concern for public finance and economic growth.\textsuperscript{5}

II. Conceptual framework of the dynamic temperature-fertility relationship

Temperature exposure could affect birth rates across several months through a variety of mechanisms. On the reproductive health side, prior work suggests semen quality is worse and testosterone levels are lower in the summer months (Levine, 1991; Dada, Gupta, and Kucheria, 2001; Chen et al, 2003; Svartberg et al, 2003). Exposure to heat increases body temperature and may lead to irregular menstruation, ovulation, or failed implantation (Meade and Earickson, 2000). Temperature extremes increase physiological energy demands, which could impact ovulation (Ellison et al, 2005).\textsuperscript{6}

On the coital frequency side, extreme heat could raise physiological cost of coitus or affect hormone levels and sex drives. Temperature may affect time use and behavior and, in turn, impact mixing rates among potential partners.\textsuperscript{7} Using recent data from the American Time Use Survey, Graff Zivin and Neidell (2014) find individuals substitute away from outdoor work and leisure at high temperatures. Individuals may time coitus to maximize infant health outcomes or minimize the costs of pregnancy.\textsuperscript{8} Given we lack information on reproductive health and coital frequency, our model cannot definitively differentiate between these mechanisms.

\textsuperscript{5} For example, low fertility rates can lead to funding problems with social insurance programs (e.g. Social Security) (Goss, 2010).
\textsuperscript{6} Temperature could indirectly impact nutritional intake via impacts on food production, though the effects could be delayed since the growing season lasts months for most crops (Schlenker and Roberts 2009).
\textsuperscript{7} 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 peak in December among romantically linked couples.
\textsuperscript{8} Using the National Survey of Family Growth, Rodgers and Udrey (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 respondent reports of April and May as the best time to have a child and December and January as the worst. Rodgers and Udrey hypothesize that due to the mismatch between expected and realized conception month, women have children later than expected, the misinformed reproducer hypothesis. Given our research design focuses on unexpected weather conditions, however, this would only be relevant if a current weather shock affects expectations about future weather.
Regardless of the mechanism, a fall in conceptions due to exposure to a temperature shock is expected to reduce births *approximately* 9 months later.\(^9\) If individuals substitute coital frequency from the month of the temperature shock to later months, however, we might observe a rebound in births 10+ months after exposure. Importantly, we could even expect a rebound in births 10 months after the initial decline in conceptions *holding reproductive health and coital frequency constant*. Providing no credit constraints or preferences for conceiving (or engaging in risky behavior) in particular calendar months, the susceptible population that failed to conceive in the month of the temperature shock would then go on to increase the susceptible population in the subsequent months. Alternatively, if the temperature shock has a lasting negative effect on reproductive health, we could continue to observe a decline in births 10+ months later. (We present a more formal temperature-fertility model in Appendix Section C to illustrate the dynamics.)

Temperature shocks could also impact the timing of births via gestational length and fetal losses (Lam, Miron, and Riley, 1994; Dadvand et al, 2011; Strand, Barnett, and Tong, 2011).\(^10\) The impacts on gestational length depend on the critical exposure period. To the extent exposure at the time of conception matters, we could see a reduction in births 9 months later but an increase in births in earlier months as the risk of premature birth increases. To the extent that exposure matters in the latter period of pregnancy, we might see an increase in births in conjunction with the temperature shock and fewer births in subsequent months. Similarly, the effect of fetal losses depends on the critical exposure period. For example, a weather shock in the first month of pregnancy could lead to an increase in fetal losses and fewer births 8 months later. If the population suffering fetal losses becomes susceptible to pregnancy again in the subsequent month, we might also observe an increase in births 10+ months after exposure.

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\(^9\) In the 2004 sample averages, approximately 2% of births fall 7 calendar months after the last normal menses, 15% fall 8 calendar months later, 68% fall 9 calendar months later, and 15% fall 10 calendar months later.

\(^10\) Temperature could affect pregnancy outcomes via parasitic or vector-borne infections, though this is less of a concern for our study setting. For example, the mosquito-borne disease malaria was effectively eradicated from the United States in the early 1940s (Barreca et al. 2012).
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, used machine-readable Natality Files for the years 1968-2004, and collected birth counts from the CDC’s online National Vital Statistics System for the years 2005-2010. The monthly birth counts are reported by state of residence except for the 1931-1941 period, when only state of occurrence is available.

We construct state-by-month daily average birth rates by dividing the average daily birth counts by the total estimated population in that state and year. 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 daily birth rate, though our results are robust to using daily birth rates in levels.

The data also permit an analysis of maternal and child characteristics. We have state-by-month birth counts by race, although these data are only available in the historical Vital Statistics reports starting in 1942. For the years 1968 through 2010, we test for impacts by birth order, age of the mother, and education level of the mother using data mostly from Natality files.

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11 We are missing birth counts for Texas in 1931 and 1932 because Texas was not part of the Vital Statistics “Registration States” until 1933. We drop Alaska and Hawaii from the sample since they entered our sample as states in 1959 and 1960, respectively.

12 Note that 1931 is the first year that birth counts are available at the state-month level. Data with finer geographic detail are not available in the earlier part of our sample. For example, county-month birth data are not available until 1968 with the detailed Natality Files.

13 The machine readable Natality Files were downloaded from the NBER website. The first year of the data is 1968. In the earlier years, some states’ data are 50% samples, so we weight these births by 2. Starting in 2005, state identifiers are no longer publicly available in the Natality Files, which is why we use the CDC’s aggregate statistics.

14 State of residence is the preferred measure since migration could be endogenous to temperature.

15 New Jersey issue data is missing birth counts by race in 1962 and 1963. According to notes in the National Vital Statistics Reports they were not collected for those years.

16 The machine-readable Natality files do not report state of residence after 2004. Therefore, we relied on CDC’s online National Vital Statistics System for birth outcomes between 2005-2010.
Starting in 1968, we explore impacts on birth outcomes, including birth weight and gestational length. We test for impacts on neonatal mortality rates over the 1959-2004 period using the Multiple Causes of Death files.\textsuperscript{17}

\textit{Weather data}

The primary weather data come from the National Climatic Data Center’s Global Historical Climatological Network (GHCN). The GHCN have daily station information on minimum temperature, maximum temperature, and precipitation over our sample period (1931-2010). The GHCN data have geographic coverage across the continental United States and include an impressive number of weather stations: there were 1,181 stations in 1930 and 3,497 stations in 2010.\textsuperscript{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.\textsuperscript{19} Importantly, we create the weather measures at the station-day level before aggregating to the state-month level to preserve non-linear effects (e.g. days above 90 F).

We also 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").\textsuperscript{20} The humidity variable has poor coverage prior to 1945, so we only control for

\textsuperscript{17} Note that the mortality data are not linked to birth records. However, this is not a serious limitation since we are concerned with estimating neonatal mortality rates, or death rates for children within 28 days of birth. Therefore, measurement error regarding period of conception is likely to be limited. Note that linked birth-death data do exist, though the data are only available for select years: 1983-1991 and 1995-2004.

\textsuperscript{18} We exclude stations for the entire year if they are missing temperature readings more than 1% of the year.

\textsuperscript{19} We linearly interpolate county population between the decennial censuses up until 1968. Starting in 1969, we use county population estimates from SEER.

\textsuperscript{20} Specific humidity is a better proxy for indoor health conditions than relative humidity because relative humidity is a function of outdoor temperature, while specific humidity captures the absolute amount of water vapor in the air.
humidity in a robustness check. Nonetheless, to the extent that humidity and temperature are naturally correlated, our temperature estimates incorporate some of the effects of humidity.\footnote{Barreca (2012) shows that failing to control for humidity causes little bias on the aggregate, but may be more important for estimating distributional (or heterogenous) effects across regions.}

**Summary statistics**

Table 1 presents the summary statistics. There were approximately 4.73 daily births per 100,000 residents on average during our sample period. Birth rates were lowest in Northeastern states and highest in Southern states: temperature and birth rates are positively correlated across regions on average. However, this positive relationship cannot be used to infer causal effects since many other factors, including poverty rates, also correlate with region. These omitted variables highlight the importance of using within-state changes in temperature to identify causal impacts.

Seasonality in birth rates varies considerably across region. Panel A of Figure 1 presents the mean of the log daily birth rate, by census region, over our sample period. In every region, birth rates peak in September: individuals are more likely to conceive between October and January. Seasonality is greatest in the South, where September birth rates are approximately 15 percent higher than May birth rates. The differences in seasonality across regions also suggest that temperature plays a role in the timing of births, given the South is generally warmer the rest of the United States. Again, however, omitted variables hinder our ability to infer causality. Other seasonal factors, like demand for agricultural labor, could account for different birth seasonality across states. Our empirical model mitigates this type of concern by including state-by-calendar-month fixed effects.

Panel B of Figure 1 indicates the seasonality in birth rates declined significantly over time. As a simple illustration, we break our sample into three time periods: 1931-1949, 1950-1979, and 1980-2010. During the 1931-1949 period and the 1950-1979 period, the daily birth rate was approximately 10% higher in September than in April. The difference between the April and September daily birth rates was closer to 5% during the 1980-2010 period. The temperature-
fertility relationship dampened significantly towards the end of the 20th century, something we estimate more formally below.

IV. Methodology

To identify causal impacts, our model relies on plausibly random variation in the temperature for a given state and calendar month. More formally, we estimate the following model via OLS:

$$Y_{st} = \sum_{k}^{K} \beta^k f(TEMP)_{s,t-k} + \gamma X_{st} + \alpha_{sm} + \delta_{t} + \theta_{dy} + \pi_{sm} * t + e_{st}$$

where $Y$ is the log of the birth rate in state $s$ at year-month $t$. $f(TEMP)$ is a semi-parametric temperature function that captures the distribution of daily temperatures in state $s$ over the set of months $K$ leading up to month $t$. $X$ is a vector of precipitation controls. $\alpha$ is a state-by-calendar-month fixed effect: unusual temperatures in a given state and calendar month identify our model. Year-by-calendar-month fixed effects ($\delta$) and census division-by-year fixed effects ($\theta$) help account for temperature changes over time that correlate spuriously with demographic changes at a national level. $\pi$ is a set of state-by-calendar-month quadratic time trends to mitigate potential biases from convergence in seasonality across states over time. We cluster standard errors at the state level to allow for serial correlation in the errors. We weight by state-year population to improve precision.

We design the temperature function $f(TEMP)$ to account for possible non-linear effects in temperature. We vary the functional form of TEMP in two key ways. First, we use a polynomial spline in the daily mean temperature, with knots at 10, 30, 50, 70, and 90 F (-12, -1, 10, 21, and 32 C). Second, we use a binned approach where we control for the fraction of the month with daily mean temperatures <30, 30-40, 40-50, 50-60, 70-80, 80-90, >90 F, with the fraction of the month with temperatures between 60 and 70F as the omitted category. Estimates are qualitatively

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22 We control for the fraction of days in the month with between 0.01 and 0.50 inches, 0.51 and 1.00 inches, and over 1.01 inches. The omitted category is the fraction of the month with no precipitation.
similar across these two specifications. We make the spline model our core specification since the standard errors are more precisely estimated.

In our core model, we test for temperature shock effects on birth rates up to 18 months (K) after exposure (see Section II for more discussion on the importance of accounting for these dynamic effects). We also estimate the impact of temperatures on births 1 to 3 months prior as a placebo check since these temperatures were realized after delivery.

As a robustness check, we use diurnal temperatures in place of daily mean temperatures. This specification accounts for 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 humidity in one specification check. To our knowledge, we are the first to estimate the impact of humidity on birth rates.

V. Birth rates

Core results

Figure 3 presents the temperature-fertility response function for 9 months after birth for the full time period, though we control for other months’ exposure. We observe an economically large and statistically significant decrease in births from exposure to high temperatures. For example, one additional day at 95 F (35 C), relative to one 65 F (18 C) day, reduces the birth rate 9 months later by 0.7\(^{24}\). Low temperatures have little effect on birth rates. At each month of exposure,

\(^{23}\) We linearly interpolate the fraction of the day in a given temperature range using the maximum and minimum temperature for a given station-day.

\(^{24}\) A direct comparison of our estimates to previous work is difficult due to differences in research designs. Nonetheless, we compare the magnitude of our estimates to those presented in Lam and Miron (1996), the most rigorous study to date. Lam and Miron (1996) models the effects of average monthly quadratic temperature in months 9 and 10 on birth rates, but the model is estimated separately by state and race. For whites in Georgia, Lam and Miron find that a 10 F increase in monthly temperatures reduces birth rates 9 months later by 7\% at 90 F, but only 4\% at 75 F. We find that an increase in daily temperatures of 10 F reduces birth rates by about 6\% at both 75 F and 90 F (0.002 log points x 30 days).
we can rule out effect sizes of +/- 0.1% from exposure to one additional day at 15 F (-9 C) relative to 65 F (18 C). The shape of the relationship suggests more rigid functional forms would not fit the data as well.\textsuperscript{25}

Figure 4 explores effects across a larger set of exposure months. In the interest of space, we focus on the marginal effects of one 95 F day. The estimated effect size for month 9 is, by construction, identical to that in Figure 2 (0.7%). Each additional 95 F day causes birth rates to fall by 0.1% in month 8 and 0.4% in month 10, both statistically significant at the five-percent level.

Importantly, we observe an economically meaningful “rebound” in births 11, 12, and 13 months after exposure. For example, one 95 F day causes a 0.2% increase in births 12 months later. The cumulative effect of a temperature shock over months 8-10 is a 0.012 decrease in log births, while births rebound by approximately +0.005 log points over months 11-13. We also observe a 0.002 log point increase in births over months 14-18, though only the estimate at 17 months is statistically significant. This suggests individuals who fail to conceive or suffer a fetal loss go on to conceive in subsequent months. That we do not observe a full recovery suggests affected individuals may be credit constrained in some months or have preferences for conceiving (or engaging in risky sexual behavior) in certain calendar months.\textsuperscript{26} If this is the case, individuals may substitute conceptions across years, something our model does not capture.

The fact the largest effect is observed 9 months after exposure is consistent with a contemporaneous fall in conception probabilities. The magnitude at month 8 relative to month 9 is fairly in line with distribution of gestational lengths observed in the data. For example, in the 2004 Natality data, 15% fall 8 calendar months later, or about one fifth the magnitude, which is similar to the one seventh we estimate. The 8- and 9-month estimates are even closer in line if some of the births at 8 months shifted into month 9.

\textsuperscript{25} Appendix Figure 1 shows estimates for a model with quadratic in monthly temperature, as used by LM.
\textsuperscript{26} Appendix Figure A2 tests the hypothesis that there are calendar-month constraints by exploring impacts out to 24 months. We find some, albeit statistically insignificant, support for the hypothesis that the initial fall in conceptions is offset by an increase in conceptions 12 months later, which is manifested as an increase in births 21 months.
The estimated magnitude at month 10 in relation to month 9 offers insights into potential mechanisms. Given about 15% of births span 10 calendar months and 68% span 9 calendar months (2004 Natality Data), we would expect the coefficient at 10 months to be about one fifth the magnitude at 9 months assuming a one-time fall in conceptions. Instead, the coefficient is over one half the magnitude. Even assuming all the births at 8 months were displaced into month 9, the coefficient would still be half the magnitude (0.004/(0.007+0.001)). There are two possible explanations for the large effect size at 10 months. First, the fall in births were made up disproportionately of first births, which typically have longer gestational lengths. Second, extreme heat affects reproductive health for up to two months (or reproductive cycles). Using Natality data (below), we find support for the first hypothesis, though we cannot rule out the second.

We also find suggestive evidence temperature shocks reduce gestational lengths for pregnancies that are near term. Specifically, one 95 F day causes a statistically significant increase in births of 0.1% in the exposure month (month 0). We observe an economically equivalent, but not statistically significant, 0.05% decrease in births one month after exposure (month 1). Using Natality data (below), we provide additional support for the hypothesis that extreme temperatures reduce gestational lengths for births that are near term.

Importantly, we find that temperature has no discernable effect on births that occurred prior to the weather realization (e.g. month -3). Our empirical model appears to be free of bias from spurious time trends.

These estimates are an economically meaningful predictor of seasonal birth rates. For this projection, we take the core estimates and apply them to the average distribution of temperatures over our sample period. Figure 5 illustrates the predicted values follow a nearly identical pattern, with births at a trough in April and a peak in August. The model does underestimate 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. That said, the model

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27 In the 2004 Natality data, 17.3% of first (live) births went 10 calendar months compared to 13.0% among higher order births.
still explains approximately half of the variation ($R^2 = 0.47$) when correlating the predicted points to the actual points in Figure 4.

Results are robust to different model specifications. We estimate the effects of exposure to a temperature in 10 F bins (<30, 30-40, 40-50, 50-60, 70-80, 80-90, >90 F). Appendix Figure A3 reports the marginal effects of one additional day above 90 F. The estimates are qualitatively similar. We also estimate a binned model where the bins capture the frequency of the month where the *diurnal* temperature is within a 10 F bin, with temperatures above 100 F and below 0 F as the categories at the bounds (Appendix Figure A4). The qualitative relationship is comparable when using diurnal temperatures, though estimates are slightly skewed in the positive direction. We test robustness to dropping both state-month time trends and division-by-year fixed effects, and with the outcome in levels (Appendix Figure A5). The estimated relationships are qualitatively similar, though estimates fail to pass the placebo test when we omit the state-month time trends. Finally, we show estimates using birth rates in levels (Appendix Figure A6).

*Heterogeneity over time*

We explore changes in the temperature-fertility relationship over time in order to glean broad lessons regarding the scope for adaptation. We restrict our sample to 10-year periods, so we omit the state-month trends from the model to improve precision. In our by-decade analysis, Figure 6, we focus on the marginal effects of 95 F days 9 months after exposure only. The marginal effect of each 95 F day is relatively stable between the 1930s and 1960s. Exposure to one additional 95 F day causes the birth rate 9 months later to fall by about 1.0% in before 1970. The effect sizes are cut in half by the 1980s, where one additional 95 F day causes the birth rate 9 months later to fall by less than 0.5%.

This general dampening of the temperature-fertility relationship follows the changes in the temperature-mortality relationship over this time period. Barreca et. al (2013) show adoption of air conditioning can explain almost all of the changes in the temperature-mortality relationship. We test the hypothesis air conditioning also explains changes in the temperature-fertility relationship in section VIII below.
Figure 7 revisits the effects of each 95 F day by exposure month during the 1931-1970 (Panel A) and 1971-2010 (Panel B). Effect sizes are larger in magnitude in the earlier period, though the dynamic relationship is qualitatively similar. Specifically, effects are largest 9 months on, though there is a statistically significant and economic significant relationship at 10 months. The rebound in births begins 11 months on, but the rebound does not fully mitigate the decline in births between 8 and 10 months.

In Appendix Figure A7, we report the effects of extreme cold. In the earlier period (1931-1970), we find each 15 F day causes a relatively small, but statistically significant, decrease in births 9 months later of about 0.005%. However, this effect reverses in the latter period (1971-2010). Each cold (15 F) day causes a nearly 0.01% increase in births 9 months later. One possible explanation is that improvements in home heating over this time period affected reproductive health and/or coital frequency. We leave this exploration for future work.

*Heterogeneity by climate, humidity*

To investigate the role of adaptation, we split our sample in half based on each state’s average exposure to days above 80 F. (Appendix Figure 8 tests for impacts across census regions.) Figure 8 shows that, in the earlier period, the magnitude of the effect is only slightly smaller in the “hot states” than “cold states”. For example, one 95 F day causes a 1.0% decrease in births 9 months later in hot states (Panel A.1) versus a 1.2% decline in cold states (Panel A.2). Estimates are smaller in magnitude in the latter period for both sets of states, and effect sizes are still only somewhat smaller in the hot states (Panel B.1). However, the magnitude of the standard errors for the cold states (Panel B.2) precludes drawing strong conclusions.

We estimate the effects of temperatures and humidity in Appendix Figure A9. Due to data limitations with the humidity variable, we restrict our sample to the 1945-2010 period. The estimated effects of hot temperatures are slightly diminished (relative to Figure 2). With respect

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28 Specifically, we control for daily specific humidity (i.e. grams of water vapor per kilogram of air) as a 6th order polynomial spline.
to humidity, one “high humidity day” at 19 grams of water vapor per kilogram of air (g/kg) leads to 0.4% decrease in births 9 and 10 months later in the earlier time period.\(^{29}\) Like cold temperatures, low humidity levels (not reported) are not a strong predictor of birth rates.

*Heterogeneity by race*

We explore impacts by race in Figure 9, where we again divide our sample up into pre- and post-1970 time periods. Due to data limitations, the by-race analysis begins in 1942. Effect sizes are greater in magnitude for non-whites. For example, each additional 95 F day reduces birth rates 9 months later by 1.0% for whites (Panel A.1) compared to 1.5% for non-whites (Panel A.2) in the earlier period. This fact suggests white women were modestly better at adapting to climate shocks, possibly via differences in income or wealth.

These racial differences, in relative terms, did not decline over time. In the 1971-2010 period, each additional 95 F day reduces birth rates 9 months later by 0.4% for whites (Panel B.1) compared to 0.7% for non-whites (Panel B.2). Exposure to hot days leads to a statistically significant increase in non-white births of 0.2% in the month of birth, suggesting impacts on gestational length may be more relevant for non-whites. The apparent effect on gestational length is also modest and positive for whites, though not statistically significant.

**VI. Impacts on maternal characteristics and infant health**

In this section, we analyze the effects of temperature on maternal characteristics and infant health outcomes. For these analyses, we rely on the machine-readable Natality files, which begin in 1968. We do not know of any other infant health data at the state-month level prior to 1968.

*Maternal characteristics*

\(^{29}\) Note the average state experiences 3 days per year above 18 g/kg.
Figure 10 explores the impacts by age of the mother. For this analysis, we construct population denominators for the respective age group. The effect size is qualitatively similar across all age groups: one additional day at 95 F causes close to a 0.5% decline in births 9 months later for 15-19, 20-24, 25-29, and 30-39 years old mothers. The similarity in magnitudes suggests that we can rule out risky behavior among the young as the predominant channel.

Figure 11 presents the marginal effect of one additional 95 F on various maternal characteristics. We find exposure to extreme heat is more likely to impact women of low socioeconomic status (SES), although the magnitudes are small and mostly confined to 9 months after exposure. Specifically, extreme heat leads to a statistically significant 0.06 percentage point decline 9 months later in the probability the mother has less than a high school education (Panel A) relative to a baseline average of 23% mothers. Conversely, we observe a significant 0.07 percentage point increase in the probability the mother has some college (Panel B) or about an increase of 0.2% relative to the average of 39%. Taken with analysis by age groups, these estimates suggest we can rule out risky behavior as the main mechanism.30

There is also a decline in births 9 months later in the probability that the father’s age is missing from the birth certificate (Panel C), a proxy for lack of paternal support. However, estimates for "father’s age missing" are skewed negatively, so we cannot draw strong conclusions regarding this outcome. We observe a statistically significant decline in the probability of first births in month 10, which is consistent with the larger than expected decline in births in month 10 relative to month 9 (Panel D).

We do not observe these low SES women giving birth in later months (e.g. month 11) as might be expected given the temporal shift in births observed above. One possible explanation is that the low SES mothers are credit constrained and have strong preferences for conceiving (or engaging in risky sexual behavior) in certain months. This possibility is also consistent with the fact that we do not observe a full rebound in births. However, the magnitude of the standard errors precludes drawing strong conclusions in this regard.

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30 Appendix Figure A14 interacts temperature with access to legal abortions. This test also implies that risky behavior is a relatively unimportant mechanism.
Infant health outcomes

We next investigate the relationship between extreme heat and two important infant health outcomes: birth weight and gestational length. (The effects of cold temperatures are available in Appendix Figure A10: results suggest cold has little impact on birth outcomes.) As Figure 12 illustrates, we observe better birth outcomes from exposure to extreme heat in month 8. For example, each 95 F day leads to a statistically significant 0.03 percentage point decrease in preterm delivery (Panel A) and a 0.02 percentage point decrease in the probability of low birth weight (Panel B). Taken with the decline in birth rates at 8 months, this improved health is suggestive of fetal losses among unhealthier fetuses. However, we cannot definitively rule out maternal selection since we observe relatively fewer low-SES mothers giving birth in month 8 (Figure 11).

Extreme heat correlates with worse health outcomes 9 and 10 months from exposure. For example, we observe a 0.02 percentage point increase in the probability of pre-term delivery (Panel A) and a 0.01 percentage point increase in the probability of low birth weight (Panel B) 10 months out. The effect sizes are small given approximately 8.4% of births are pre-term, and 12.7% are low birth weight. One explanation is that the individuals who would have given births prematurely at 8 months, went onto conceive in the two months following the month of exposure. This explanation seems plausible given the decline in pre-term deliveries at month 8, and the fact the timing between exposure and delivery for births at 10 months is much longer than 37 weeks (i.e. the cutoff for pre-term delivery). However, the positive selection of maternal characteristics (observed above) suggests we should observe better birth outcomes 9 and 10 months later. Also, given similar magnitudes (but opposite signs) at month 8 and month 9, there would need to be a 1-to-1 shift in births for the entirety of the effect to be due to displacement.

With regards to impacts on prenatal health near the end of term (presumably the third trimester), we do observe exposure to temperature extremes in the month of birth (month 0) correlates with lower birth weight and shorter gestational lengths. For example, each additional 95 F day in the
month of birth causes an increase in pre-term deliveries by close to 0.02 percentage points (Panel A) and a 0.01 percentage point increase in low birth weight (Panel B). The evidence suggests we can rule out forward displacement in unhealthy births is driving the lower birth weights at month 0. Specifically, we do not observe better birth weights one month from exposure; in fact, we actually observe an increase, albeit statistically insignificant, in the probability of low birth weight at month 1. We do not observe worse birth outcomes 3 to 5 months after exposure, suggesting exposure in the second trimester is less important. Our findings for third trimester, but not second trimester, are consistent with Deschenes et al. (2009).

To investigate the fecundity channel, we look at the impacts on sex ratio. Recent research provides compelling evidence female fetuses are more resilient to in utero health shocks (Trivers Willard, 1973; Sanders and Stoecker, 2015). If extreme heat affects fecundity, we expect an increase in the proportion of births that are female. In general, the estimates are too imprecisely estimated to draw meaningful conclusions. However, estimates suggest male births are more likely to experience reduced gestational lengths or forward displacement near the end of term. Specifically, there is a 0.01 percentage point decrease in the probability the child is female in month 0, and roughly a 0.01 percentage increase the month after (month 1). The estimates in later months are too imprecise to draw meaningful conclusions.

In Panel D, we investigate the relationship between temperature and neonatal mortality (deaths <28 days from birth) for the 1959-2004 period. We focus on neonatal mortality since we do not have information on date of birth, and we can reasonably differentiate between pre- and post-natal exposure. We find each day at 95 F correlates with a 0.7% increase in the neonatal mortality rate 9 months later. One possibility is, given the positive selection at month 9, the estimate is a lower bound on the causal effect of exposure around the time of conception. We find exposure to extreme heat in the month of death and the month preceding death lead to an increase in neonatal mortality, though only statistically significant at the 10% level. These estimates further corroborate the findings that exposure to extreme heat around both the delivery term and the time of conception are sub-optimal for infant health. We also see a fall in neonatal

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31 Birth counts by gender are not available prior to 1942 or between 1960 and 1967. As such, we restrict our analysis to the period from 1968 on.
mortality from exposure at month 5 and 6, which is potentially consistent with fetal losses among the less healthy. The decline in neonatal mortality at months 5 and 6, accompanied by the increase in neonatal mortality at month 9, suggest a temporal displacement in the birth of these unhealthier infants. However, we do not observe a statistically significant decline in births in months 5 and 6, so the evidence on fetal losses and temporal displacement is mixed.

Discussion: Seasonality in births and infant health

Our model shows temperature can explain only a small portion of the relationship between season of birth and infant health outcomes. Figure 13 plots the actual variation in pre-term delivery (Panel A) and low birth weight (Panel B) alongside the predictions using our temperature estimates. Our estimates do well to predict the trough in both variables around March and the increases in health risks through June. However, the predictions do not fit the subsequent fall in health risk in September, and the increase thereafter through January. Note our model predicts the trough since our estimates show better health outcomes 8 months after exposure (possibly due to fetal losses), but worse health outcomes 9 months from exposure due to high temperatures. However, our estimates over-predict worse health outcomes for summer births due to exposure near delivery term.\(^{32}\)

The conclusions drawn here are somewhat different, though not in conflict, with Buckles and Hungeman (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, as opposed to weather at conception, is a better predictor of seasonality in maternal characteristics. To test their hypothesis, they make the assumption that weather 12 months prior to birth is a good proxy for expected weather at birth. BH show weather 12 months prior to birth is a stronger predictor of seasonal maternal characteristics than weather 9 months prior.\(^{33}\)

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\(^{32}\) Recent work by Currie and Schwandt (2013) suggests maternal selection is not the driving factor. Specifically, they show that spring conceptions (or winter births) have better health outcomes even when comparing outcomes within mothers. The authors hypothesize disease exposure (e.g. influenza) late in the pregnancy could be adversely affecting spring births.

\(^{33}\) BH’s controls include average minimum temperature, average maximum temperature, days above 90 F, and degree departure from normal temperature. Thus, BH’s model does account for non-linear effects in daily temperatures to the same degree as our model.
Conversely, our analysis suggests the weather 12 months prior is likely related to births through a shift in conceptions due to high temperatures. That said, we estimate our model from unusual variation in the temperature for a given state and month, unlike BH whose model is partially identified from some fixed differences in seasonality across counties. While our model can explain substantial portion of the seasonal variation in birth rates, the remaining variation may still be driven by expected weather conditions and a mechanism consistent with what BH propose.

VII. Climate change projections

Our climate projections come from the Hadley CM3 model. We use the A1F1 scenario, which assumes no concerted reduction in greenhouse gas emissions, often referred to as the “business as usual” scenario. The unit of observation is day by grid point, where grid points are spaced out every 2.5 degrees latitude and 2.5 degrees longitude, respectively. Variables include minimum temperature, maximum temperature, precipitation, and specific humidity. We aggregate Hadley data to the county level using inverse distance weights. Then, we aggregate data up to the state level using county population in 2000 as weights. Finally, we adjust predictions to account for the fact that the Hadley model predicted warmer weather than actually realized during the earlier years of the model run.

The Hadley CM3 model projects a substantial increase in the frequency of hot weather. Appendix Figure A11 illustrates the projected changes in the distribution of daily temperatures between the 1990-2002 period and the 2070-2099 period. The model projects 40 more days per year with daily mean temperatures above 90 F. The disproportionate increase in high temperatures highlight the importance of allowing for non-linear effects in our core empirical specification. Using the bias-adjusted Hadley CM3 A1F1 model and estimates from Figure 4

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34 Degrees vary in distance depending on the latitude. For example, a 2.5 degree change in latitude (longitude) is roughly 150 (111) miles around Chicago and 170 (130) miles around New Orleans.

35 We use the 1990-2002 time period as the baseline since the climate model data begin in 1990. And, we do not have access to data after 2002 since the data are no longer publicly accessible.
Panel B, we project that annual birth rates will decline by about 3% (statistically significant at 5% level). The model projects a 5.1% decline in the West South Central United States (e.g. Louisiana), given the disproportionate increase in high temperature days there. Given poverty rates are higher in the South, climate change will have important distributional impacts.

As another thought experiment, Panel B predicts the expected impacts on cumulative birth rates if we were to use our estimates from the 1931-1970 period. These estimates suggest a more substantial decline in birth rates of about 5% (statistically significant at 5% level). This conforms to expectations that developing countries are more likely to be impacted by climate change.

Table 2 presents the projections using models with 10-degree temperature bins (Panel C), diurnal temperatures (Panel D), and controlling for humidity (Panel E). The model with temperature bins and diurnal temperatures project similar effect sizes. However, the model controlling for humidity projects effects close to twice the size, with a decline in birth rates as large as 10.5% in the West South Central. Consistent with previous research on mortality (Barreca 2012), these estimates suggest that accounting for humidity has important implications for understanding distributional impacts. Using the unadjusted climate projections (Panel F), we find slightly larger impacts as could be expected (see Appendix Figure A12 for comparison of bias-adjusted and unadjusted climate projections).

The estimated effect on annual birth rates masks important changes in birth seasonality. As Appendix Figure A12 illustrates, the predicted increases in days above 90 F (by month) disproportionately fall during the summer months. For example, the Hadley model predicts 10 more days above 90 F during August (on average). Given our estimates, we expect births to fall in the spring and early summer months relative to late summer and early winter. Figure 14 illustrates this fact using the estimates from our two different sample periods. Assuming the temperature-fertility response function from the 1971-2010 period, there will be close to an 8% fall in April births, with roughly no impact on August births.36 Using our estimates from the

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36 We do not see an increase in births in the summer months because the increase in warm weather during winter months helps offset the shift in conceptions from summer to winter months. See Appendix Figure A7 for illustration of the positive effect of cold temperatures on births.
1931-1970 period, we project a sizable 20% decline in births in April, with a modest 5% increase in births in August.

VIII. Air conditioning and the temperature-fertility relationship over time

As Figure 4 documents, there was a substantial decline in the temperature-fertility relationship starting in the 1970s. Here, we explore whether air conditioning (AC) can explain some of this decline. The 1960, 1970, and 1980 Decennial Censuses include information on residential AC coverage by state of residence.\(^{37}\) Given the limited time coverage on the AC data, we restrict our sample to the 1950-1990 period to mitigate measurement error. AC coverage was linearly interpolated from the 1960, 1970, and 1980 Censuses. We assume air conditioning coverage was zero as of 1950, and use the growth rate in AC coverage between 1970 and 1980 to project out to 1990.\(^{38}\) (Appendix Figure A13 illustrates the trends in coverage, with a special point to show that adoption was quickest in the south.) Our work builds on Siever (1985, 1989), which correlated changes in birth seasonality between 1947 and 1980 with the adoption of air conditioning. Here, we extend Siever’s work by correlating changes in the temperature-fertility response function explicitly, making our work is better suited to addressing the causal channel through which air conditioning could affect birth rates.

Since variation in air conditioning adoption is potentially endogenous, we also control for the main effect to mitigate omitted variables bias. We assume the correlation between the modifier and any omitted variable is independent of temperature throughout the year. We control for the interaction between the temperature variables and a time trend to mitigate concerns the modifier correlates with a general reduction in susceptibility to temperature extremes. In the interest of brevity, we present the coefficients on the AC-temperature interaction only. We use a more parsimonious set of lags and only allow weather to affect births in months 0, 1, and 8 through 13. All other controls are the same as equation (1).

\(^{37}\) We define “air conditioning” as at least one air conditioning unit or a central air conditioning.

\(^{38}\) To the extent the measurement error in our air conditioning variable is classical, 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.
We find air conditioning substantially mitigated the temperature-fertility response function. In the interest of space, we present the effects of one additional 95 F day, interacted with AC, on births 9 months later. At zero AC coverage in 1950, each additional day at 95 F reduces the birth rate by approximately 0.012 log point (Panel A). At 72% air conditioning coverage, the estimated AC coverage in 1990, the AC-temperature interaction mitigates the impact of one 95 F day by 0.005 log points (0.72% x 0.007 log points). As such, AC can account for about half the decline in the temperature-fertility relationship between 1950 and 1990, which was around 0.008 log points. (0.0012-0.008=0.004. The effect of one 95 F day was approximately 0.004 log points as of 1990s, as illustrated in Figure 6.) Thus, the estimate is economically meaningful, though not as large in magnitude as the impact of AC on the temperature-mortality relationship (Barreca et. al 2013). In Appendix Figure A14, we show that educational levels of women, nutritional intake via Food Stamps, and access to legal abortions have little modifying effect.

Our AC estimates suggest air conditioning could help mitigate birth seasonality and improve birth outcomes. However, an increase in energy consumption from air conditioning could exacerbate greenhouse gas emissions and climate change. Thus, air conditioning should be adopted as part of a mix of strategies that possibly include a reduction in energy consumption elsewhere in the economy. Such an analysis would require a greater understanding of the costs and benefits of reducing energy consumption elsewhere. Our estimates could be useful for such a comprehensive cost-benefit analysis.

**IX. Conclusion**

In the United States, high ambient temperatures have a statistically and economically significant impact on both total births and birth timing. Specifically, we find unusually high temperatures cause a fall in births approximately 8 to 10 months later, followed by a modest rebound in births in months 11, 12, and 13. The largest effect is at 9 months: each additional day with a mean temperature of 95 F (relative to one day at 65 F) causes the birth rate 9 months later to decrease by 0.7%. The 9-month effect is consistent with extreme heat reducing contemporaneous
conception probabilities, though we cannot discern whether effects operate though reproductive health or coital frequency with the data at hand.

The rebound in births suggests the costs of a short-term environmental shock are mitigated in the medium term by a shift in conception month. However, there are hidden costs to this shift: more children will be born the following summer, and as a result, more likely to be exposed to hot weather in the critical third trimester. Our estimates indicate exposure to extremely high temperatures near the end of term increases the risk of pre-term delivery and low birth weight. Given the literature linking fetal health with later life outcomes (Almond and Currie 2011), we hypothesize differential exposure to high temperatures could help explain the economic disparities across the northern and southern United States, especially prior to the wide-scale adoption of air conditioning. However, future work is necessary to corroborate this hypothesis.

In addition, our estimates allow us to draw broad lessons regarding the costs of climate change in the United States. Using our estimates from the more recent sample period (1971-2010), we project a 3% decline in births. Thus, an increased frequency in high temperature days will put modest downward pressure on already-low birth rates in the United States, and possibly other developed countries.39 As a caveat, this projection is likely to represent an upper bound since it ignores low-frequency adaptations (e.g. migration) or longer-term (2+ year) shifts in birth timing. That said, any unaccounted for shift in births to later years is likely sub-optimal if agents are already timing conceptions to maximize utility, and presumably, infant health. And, assuming the trends towards women having children at later ages continues, the scope for postponing conceptions will diminish further in the coming century.40

We can also learn about potential costs of climate change for developing countries. As a thought experiment, we use the temperature-fertility relationship from the earlier sample period (1931-1970) to project the costs of climate change on the United States. Here, we project a more sizeable reduction in birth rates of 5% for the United States, with up to an 8% decline in births in

39 In “high income” countries, the fertility rate was approximately 2.5 in 1970, but only 1.7 in 2011 (World Bank, 2013). Only 13 countries had fertility rates below the “replacement rate” in 1970, compared to 81 countries in 2011 (World Bank). The replacement rate is defined as 2.1 births per female.
40 Approximately 20% of all births were to women 30 years and older in 1969 compared to 25% in 2004 (Natality data).
parts of the South. The magnitude suggests climate change could have large impacts in developing countries that resemble the mid-to-early-20th century United States. Also of note, we observe a drastic reduction in the temperature-fertility relationship over our 80-year sample period. For example, the magnitude of the effect at 9 months is twice as large in the 1931-1970 period as the 1971-2010 period. We find that air conditioning can explain about half of the dampening of the temperature-fertility relationship. Echoing Barreca et al. (2013), providing low-cost access to air conditioning may be an effect tool for mitigating the costs of climate change in developing countries.

Our model represents a step forward in understanding what drives seasonality in birth outcomes in the United States, both historically and today. However, the science is far short of fully explaining observable disparities in outcomes. Back-of-the-envelope calculations suggest our flexible temperature-fertility model explains only half of the seasonal variation in births, and even less of the seasonal variation in infant health. Expanding beyond the United States, birth rates also peak in early summer in much of Western Europe (Lam and Miron 1996), a peak our model fails to predict. Recent research posits seasonal diseases (Currie and Schwandt 2013) and sunlight exposure (Wernerfelt et al. 2014) both play a role in infant health, and may help explain some of the remaining variation. Fully quantifying the impact of non-temperature seasonal factors on birth rates and infant health remains an area for future study.
References


Appendix B: Dynamic model of fertility

Take a simple model where the number of conceptions \( y_t \) in month \( t \) is a product of the susceptible population \( S_t \) and the conception probability \( p_t \), or \( y_t = S_t \times p_t \). The conception probability in month \( t \) is an increasing function of reproductive health \( h_t \) and coital frequency \( c_t \) or \( p_t = p(h_t, c_t) \). Both \( h_t \) and \( c_t \) are endogenous to current weather realizations and past weather realizations. For example, past weather can inform beliefs about expected weather conditions at time \( t \), have lasting (or lagged) impacts on reproductive health, or may cause individuals to inter-temporally substitute coital acts across months (assuming a menstrual cycle of one month). More formally, let \( h_t = h(w_t, w_{t-1}, \ldots, w_T, \alpha_m) \) and \( c_t = c(w_t, w_{t-1}, \ldots, w_T, \alpha_m) \), where \( w_t \) is the weather at time \( t \) with \( T \) being the limit of the horizon. \( \alpha_m \) is a vector of calendar month indicators that affect reproductive health or coital frequency independently of the realized weather over the last \( T \) months. For example, the cost of coitus might be lower in August when certain individuals (e.g. teachers) have vacation.

Consider the effects of a temperature shock in month \( t \) \( (dw_t) \) on conceptions. Changes in conceptions can be expressed as: \( \frac{dy}{dw_t} = S_t \frac{dp}{dw_t} + p_t \frac{dS_t}{dw_t} \). This shock cannot affect the susceptible population at time \( t \) (by design), so this simplifies to: \( \frac{dy}{dw_t} = S_t \frac{dp}{dw_t}, \) where \( \frac{dp}{dw_t} = \frac{\partial p}{\partial h_t} \frac{dh_t}{dw_t} + \frac{\partial p}{\partial c_t} \frac{dc_t}{dw_t} \). Assuming the temperature shock reduces conception probability in month \( t \) \( (dp/dw_t < 0) \), then conceptions will fall in month \( t \) \( (dy/dw_t < 0) \) with the trivial assumption that the susceptible population is greater than zero \( (S_t > 0) \). We cannot differentiate between a change in reproductive health and a change in coital frequency since we have two unknowns and only have one equation.

The effect of a temperature shock at time \( t \) could impact conceptions in month \( t+1 \), through four channels. First, the weather shock could have lasting harm on reproductive health, which would reduce conception probability in month \( t+1 \). Second, individuals could respond to a change in conception probability in the previous month by shifting coital acts to \( t+1 \), increasing the conception probability in \( t+1 \). Third, the weather shock in month \( t \) could increase the susceptible population since individuals who failed to conceive in month \( t \), will now be susceptible again in month \( t+1 \). Fourth, the weather shock could increase fetal losses in month \( t \), which could increase the susceptible population in \( t+1 \).

Regardless of a lasting impact on reproductive health or coital frequency, a weather shock at time \( t \) could impact conceptions for several months. While the susceptible population at time \( t \) is exogenous to current weather realizations, the susceptible population in the next month \( (t+1) \) is determined by the weather in month \( t \). Specifically, we assume the susceptible population in any given month carries over to the next month should they not conceive \( (S_t \times y_t) \). Also, women who suffer fetal losses in the month \( t \) \( (f_t) \) become susceptible again in \( t+1 \). Additionally, there is an exogenous change in the number of women who are susceptible \( (k_{t+1}) \). More formally, we have: \( S_{t+1} = S_t \times y_t + f_t + k_{t+1} \).

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41 It is reasonable to assume that \( dp/dw_t < 0 \) since both health \( (h_t) \) and coital activity \( (c_t) \) are likely inversely related to the weather shock.

42 In the of credit constraints by calendar month, the effects would spillover to the next year.

43 The variable \( k \) is intended to capture population aging and higher order births. The newly susceptible population could be endogenous if women become susceptible after giving birth. However, we ignore this
To better understand the dynamics of this model, let us take an example where a weather shock causes a one-time fall in the conception probability in month 0. Specifically, assume the conception probability is 0.10 in month 0 and the conception probability is 0.20 outside of month 0. Assume no fetal losses and that we are in a steady state prior to the weather shock where the exogenous change in the susceptible population \( k_t \) is equal to 0.2 times the susceptible population in the previous month. Compared to the counterfactual, conceptions would fall by 50% in month 0. This results in an increase in the susceptible population and an increase in births that fades out over time. That is, the weather shock would lead to a 10% increase \((0.5 \times 0.2)\) in conceptions in month \( t+1 \), an 8% increase \((0.5 \times 0.8 \times 0.2)\) in month \( t+2 \), and so on. Assuming a nine-month gestational length and no differential in fetal losses, this would translate into a decrease in births 9 months later and an increase in births 10 months later that fades with time. Assuming a more normal distribution of gestation lengths, centered around 9 months, the change in births 10 months on would be ambiguous. Appendix Figure B1 illustrates the one case where there is a small increase in births in month 10.

Differentiating \( y_{t+1} \) with respect to \( w_t \), we therefore have: 
\[
\frac{dy_{t+1}}{dw_t} = \frac{dp_{t+1}}{dw_t} + \frac{dS_{t+1}}{dw_t}/p_{t+1},
\]
where \( \frac{dS_{t+1}}{dw_t} = -\frac{dp_t}{dw_t} + dS_t/\frac{dp_t}{dw_t} \). Note that if we assume the weather shock reduces conception probability in month \( t \) but increases conception probabilities in month \( t+1 \), then \( \frac{dy_{t+1}}{dw_t} \) will be positive. If we assume conception probabilities fall in month \( t+1 \) due to a persistent health shock, then the sign of \( \frac{dy_{t+1}}{dw_t} \) is ambiguous without further qualification.\(^{44}\)

We can extend the model to births \( (Y_t) \), which would be a function of gestational lengths and fetal losses for conceptions over the last 9 months. Specifically, let 
\[
Y_t = \sum_{s=0}^{9} y_{t-s} \times g_{t-s}.
\]
where \( g \) is the probability that conceptions in month \( t-s \) are born in month \( t \), which is a function of past weather realizations.

\(^{44}\) In actuality, the change in births in \( t+1 \) could be positive if conception probabilities fall in \( t+1 \) so long as 
\[
\frac{dp_t}{dw_t}/p_{t+1} > -\frac{dS_t}{dw_t}/S_{t+1}.
\]
In other words, the relative fall in conception probabilities must be smaller (in absolute value) than the relative increase in susceptible population.
Figure 1: Seasonal births, by country
2000-2010

United States, Germany, and Australia

Figure 2: Daily birth rate per 100,000 residents by month

Panel A: Differences by Census region, 1931-2010

Panel B: Differences by time period

Note: Estimates using state-year populations as weights.
Figure 3: Effect of a one-day change in temperature on birth rate 9 months later
Reference category is 65 °F
1931-2010 period

Note: The spline estimates are the solid line and the dashed line represent two standard errors around the point estimates. The estimates can be interpreted as the impact, in log points, of one additional day at a given temperature relative to 65 °F on the monthly birth rate. The spline estimates have knots at 10, 30, 40, 70, and 90 °F. The point estimates give the impact of one more day at a given temperature (relative to 65 °F) on the log of the monthly birth rate (per 100,000 residents). The model has year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar month quadratic time trends, and division-by-year fixed effects. We control for fraction of days with precipitation between 0.01 and 0.50 inches, 0.51 and 1.00 inches, and over 1.01 inches for each month. In addition, we control for effects for up to 18 months after exposure (and 3 months prior to exposure as a placebo check), though we only report the estimates on month 9 here. Estimates are weighted by state-year population. Standard errors are clustered at the state-level.
Figure 4: Marginal Effect of one day with a mean temperature of 95 °F relative to 65 °F by months from exposure

Note: The brackets represent +/- two standard errors. The gray shading highlights both 0 and 9 months from exposure. See note to Figure 3 for details on the model.
Figure 5: Seasonal predictions
Outcome: Log of the birth rate

Note: The predictions are based on the model estimates across the full distribution of temperatures and exposure months. 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 6: Effects by decade of exposure
Effect of one day with a mean temperature of 95 °F relative to 65 °F on births 9 months later

Note: The brackets represent +/- two standard errors. These are the estimates from equation (1) with a spline in temperature. The model has year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar-month linear time trends, and division-by-year fixed effects. We allow for effects in months 0, 1, 7, 8, 9, 10, 11, 12, and 13 after exposure, though we only report month 9 here. We control for fraction of days with precipitation between 0.01 and 0.50 inches, 0.51 and 1.00 inches, and over 1.01 inches in each month. Estimates are weighted by state-year population. Standard errors are clustered at the state level.
Figure 7: Two sample periods
Effect of one day with a mean temperature of 95 °F relative to 65 °F

Panel A: 1931-1970

Panel B: 1971-2010

Note: See notes to Figure 4.
Figure 8: Estimates by climate of state
Effect of one day with a mean temperature of 95 °F relative to 65 °F

Panel A: 1931-1970*

Panel A.1: Hot states

Panel A.2: Cold states

Panel B: 1971-2010

Panel B.1: Hot states

Panel B.2: Cold states

Note: See notes to Figure 4. Hot states are defined as those states with more than the median frequency of days above 80 °F over the 1931-2010 sample period.
*Y-axis scale is larger in Panel A than in Panel B.
Figure 9: Estimates by race
Effect of one day with a mean temperature of 95 °F relative to 65 °F
Years 1942-2010

Panel A: 1942-1970*
Panel A.1: Whites
Panel A.2: Non-whites

Panel B: 1971-2010
Panel B.1: Whites
Panel B.2: Non-whites

Note: See notes to Figure 4. The birth rates by race are only available starting in 1942.
*Y-axis scale is larger in Panel A than in Panel B.
Figure 10: Estimates by maternal age at birth
Effect of one day with a mean temperature of 95 °F relative to 65 °F
1968-2010

Panel A: 15-19 years old
Panel B: 20-24 years old
Panel C: 25-29 years old
Panel D: 30-39 years old

Note: See notes to Figure 4. Unlike other estimates, the outcome variable is constructed using the population counts for women in the particular age group. The data by race begin in 1942. However, the data are only available by white and non-white until 1968.
Figure 11: Estimated relationship with maternal characteristics
Effect of one day with a mean temperature of 95 °F relative to 65 °F
1968-2010

Panel A: Mom has less than HS ed (x100)
Panel B: Mom has some college (x100)
Panel C: Father’s age is missing (x100)
Panel D: First live birth (x100)

Note: See notes to Figure 4. Several states do not report maternal education at one point or another during the sample period. The estimated effects are scaled up by 100 to percentage points. 23% of women have less than high-school (HS) education. 39% have some college education. The father’s age is missing on 13% of births. 40% of the sample are first live births.
Figure 12: Estimated relationship with infant health
Effect of one day with a mean temperature of 95 °F relative to 65 °F
1968-2010 (Panels A-C), 1959-2004 (Panel D)

Panel A: Gestation < 37 weeks (x100)
Panel B: Birth weight < 2500g (x100)
Panel C: Child is female (x100)
Panel D: Log of neonatal mortality rate

Note: See notes to Figure 4. The average fraction of low birth weight babies in our sample is 8.4%, per-term deliveries is 12.7%, and female is 48.8%. Neonatal deaths are of infants within 28 days of birth. The neonatal mortality rate is the average daily deaths per 100,000 live births in a given month (average=32.5). The neonatal mortality estimates span the years 1959 through 2004.
Figure 13: Seasonal predictions of birth outcomes

Panel A: Gestation < 37 weeks (x100)

Panel B: Birth weight < 2500 g (x100)

Note: The predictions are based on the model estimates across the full distribution of temperatures and exposure months. We use only the temperature estimates to make these predictions, and ignore rainfall and all other controls. The predicted and actual values should be interpreted as deviations, in percentage points, from the June average.
Figure 14: Predicted changes in birth rates by 2070-2099 by calendar month

Panel A: Using estimates from 1971-2010

Panel B: Using estimates from 1931-1970

Note: Average exposures estimated using county population estimates in 2000 as weights. The climate change predictions are "bias adjusted" to factor out the difference between the realized temperatures and model predictions for the 1990-2002 time period. The projected change in birth rates use our estimates for the 1971-2010 period with exposure in months 8 through 13 only.
Figure 15: Relationship with residential air conditioning coverage

Temperature 9 months prior to birth only
1950-1990

Panel A: Main effect of temperature as of 1950

Panel B: Temperature-A/C interaction

Note: Y-axes scales vary across panels. These are the estimates from equation (1) with a spline in temperature as a main effect, the fraction of population with residential air conditioning (A/C) as a main effect, and the temperature variables interacted with the A/C variable. We also control for time interacted with the temperature variables; the Panel A figure represents the main effect holding this year-by-temperature fixed at 1950. The model has year-month fixed effects, state-by-calendar-month fixed effects, state-by-calendar-month quadratic time trends, and division-by-year fixed effects. We allow for effects in months 0, 1, and 8 through 13, though only report month 9 here. We control for fraction of days with precipitation between 0.01 and 0.50 inches, 0.51 and 1.00 inches, and over 1.01 inches in each month. Estimates are weighted by state-year population. Standard errors are clustered at the state level.
<table>
<thead>
<tr>
<th>Sample:</th>
<th>All states</th>
<th>Northeast</th>
<th>Midwest</th>
<th>South</th>
<th>West</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily births per 100,000 residents</td>
<td>4.727</td>
<td>4.347</td>
<td>4.725</td>
<td>4.911</td>
<td>4.866</td>
</tr>
<tr>
<td>Mean temp (°F) &lt; 30</td>
<td>0.095</td>
<td>0.138</td>
<td>0.179</td>
<td>0.029</td>
<td>0.039</td>
</tr>
<tr>
<td>Mean temp (°F) 30-40</td>
<td>0.112</td>
<td>0.161</td>
<td>0.151</td>
<td>0.073</td>
<td>0.067</td>
</tr>
<tr>
<td>Mean temp (°F) 40-50</td>
<td>0.144</td>
<td>0.168</td>
<td>0.142</td>
<td>0.128</td>
<td>0.145</td>
</tr>
<tr>
<td>Mean temp (°F) 50-60</td>
<td>0.183</td>
<td>0.170</td>
<td>0.152</td>
<td>0.166</td>
<td>0.276</td>
</tr>
<tr>
<td>Mean temp (°F) 60-70</td>
<td>0.200</td>
<td>0.185</td>
<td>0.177</td>
<td>0.191</td>
<td>0.272</td>
</tr>
<tr>
<td>Mean temp (°F) 70-80</td>
<td>0.190</td>
<td>0.156</td>
<td>0.164</td>
<td>0.256</td>
<td>0.147</td>
</tr>
<tr>
<td>Mean temp (°F) 80-90</td>
<td>0.073</td>
<td>0.023</td>
<td>0.035</td>
<td>0.154</td>
<td>0.041</td>
</tr>
<tr>
<td>Mean temp (°F) &gt;= 90</td>
<td>0.003</td>
<td>0.000</td>
<td>0.001</td>
<td>0.003</td>
<td>0.013</td>
</tr>
<tr>
<td>Precipitation (1/100 inches) = 0</td>
<td>0.700</td>
<td>0.643</td>
<td>0.676</td>
<td>0.703</td>
<td>0.799</td>
</tr>
<tr>
<td>Precipitation (1/100 inches) 0-50</td>
<td>0.234</td>
<td>0.279</td>
<td>0.264</td>
<td>0.215</td>
<td>0.168</td>
</tr>
<tr>
<td>Precipitation (1/100 inches) 50-100</td>
<td>0.041</td>
<td>0.049</td>
<td>0.040</td>
<td>0.046</td>
<td>0.022</td>
</tr>
<tr>
<td>Precipitation (1/100 inches) &gt; 100</td>
<td>0.025</td>
<td>0.028</td>
<td>0.020</td>
<td>0.035</td>
<td>0.011</td>
</tr>
<tr>
<td>Number of states</td>
<td>49</td>
<td>9</td>
<td>12</td>
<td>17</td>
<td>11</td>
</tr>
</tbody>
</table>

Notes: Temperature and precipitation means represent the fraction of the days per month at a given level. Averages are weighted by state-year populations. Alaska and Hawaii are excluded from the sample.
Table 2: Climate change projections for 2070-2099 period
Change in the log of the daily birth rate

<table>
<thead>
<tr>
<th>Census Division</th>
<th>Entire US</th>
<th>New England</th>
<th>Mid Atlantic</th>
<th>E. N. Central</th>
<th>W. N. Central</th>
<th>South Atlantic</th>
<th>E. S. Central</th>
<th>W. S. Central</th>
<th>Mountain</th>
<th>Pacific</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Base predictions</td>
<td>-0.035</td>
<td>-0.024</td>
<td>-0.030</td>
<td>-0.031</td>
<td>-0.038</td>
<td>-0.038</td>
<td>-0.044</td>
<td>-0.051</td>
<td>-0.020</td>
<td>-0.018</td>
</tr>
<tr>
<td></td>
<td>(.016)</td>
<td>(.014)</td>
<td>(.015)</td>
<td>(.015)</td>
<td>(.018)</td>
<td>(.016)</td>
<td>(.019)</td>
<td>(.021)</td>
<td>(.013)</td>
<td>(.012)</td>
</tr>
<tr>
<td>Panel B: Predictions using estimates from 1931-1970 period</td>
<td>-0.055</td>
<td>-0.040</td>
<td>-0.048</td>
<td>-0.050</td>
<td>-0.061</td>
<td>-0.061</td>
<td>-0.071</td>
<td>-0.081</td>
<td>-0.031</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(.015)</td>
<td>(.011)</td>
<td>(.013)</td>
<td>(.013)</td>
<td>(.016)</td>
<td>(.016)</td>
<td>(.019)</td>
<td>(.023)</td>
<td>(.011)</td>
<td>(.01)</td>
</tr>
<tr>
<td>Panel C: Using temperature bins</td>
<td>-0.021</td>
<td>-0.023</td>
<td>-0.025</td>
<td>-0.021</td>
<td>-0.020</td>
<td>-0.027</td>
<td>-0.024</td>
<td>-0.021</td>
<td>-0.016</td>
<td>-0.013</td>
</tr>
<tr>
<td></td>
<td>(.02)</td>
<td>(.015)</td>
<td>(.017)</td>
<td>(.019)</td>
<td>(.024)</td>
<td>(.02)</td>
<td>(.028)</td>
<td>(.034)</td>
<td>(.015)</td>
<td>(.014)</td>
</tr>
<tr>
<td>Panel D: Using diurnal temperature</td>
<td>-0.039</td>
<td>-0.030</td>
<td>-0.037</td>
<td>-0.032</td>
<td>-0.036</td>
<td>-0.052</td>
<td>-0.049</td>
<td>-0.052</td>
<td>-0.022</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>(.019)</td>
<td>(.015)</td>
<td>(.018)</td>
<td>(.016)</td>
<td>(.018)</td>
<td>(.027)</td>
<td>(.02)</td>
<td>(.025)</td>
<td>(.013)</td>
<td>(.012)</td>
</tr>
<tr>
<td>Panel E: Controlling for humidity</td>
<td>-0.054</td>
<td>-0.034</td>
<td>-0.044</td>
<td>-0.047</td>
<td>-0.069</td>
<td>-0.050</td>
<td>-0.078</td>
<td>-0.105</td>
<td>-0.029</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(.021)</td>
<td>(.016)</td>
<td>(.017)</td>
<td>(.019)</td>
<td>(.027)</td>
<td>(.019)</td>
<td>(.031)</td>
<td>(.045)</td>
<td>(.016)</td>
<td>(.016)</td>
</tr>
<tr>
<td>Panel F: Using unadjusted Hadley climate data</td>
<td>-0.044</td>
<td>-0.027</td>
<td>-0.033</td>
<td>-0.041</td>
<td>-0.053</td>
<td>-0.047</td>
<td>-0.061</td>
<td>-0.070</td>
<td>-0.019</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(.015)</td>
<td>(.015)</td>
<td>(.015)</td>
<td>(.017)</td>
<td>(.019)</td>
<td>(.017)</td>
<td>(.021)</td>
<td>(.025)</td>
<td>(.008)</td>
<td>(.01)</td>
</tr>
</tbody>
</table>

Notes: All projections are relative to the climatic averages between 1990 and 2002. Panel A and B predictions use the estimates from months 7 through 18, for the respective time period, with the bias-adjusted Hadley CM3 A1F1 model. Panel C uses the unadjusted climate-change projections from the Hadley model. Standard errors are in parentheses.
Figure A1: Daily spline versus monthly quadratic
Effect of a one-day change in temperature on birth rate 9 months later
1931-2010

Note: The daily spline (solid line) is a cubic polynomial in daily mean temperature with nodes at 10, 30, 50, 70, and 90 F. The quadratic (dashed line) is a quadratic in the average monthly mean temperature. The lines are estimated in separate models, but with a similar set of controls. See notes to Figure 4 for that list of controls.
Figure A2: Longer lag of 24 months
Effect of one-day change from between 60-70 °F to above 90 °F
1931-2010

Note: See notes to Figure 4.
Figure A3: Using binned temperatures
Effect of one-day change from between 60-70 °F to above 90 °F
1931-2010

Note: See notes to Figure 4. The estimates come from a model, similar to equation (1), except with an 10 °F binned approach in daily mean temperature (<30, 30-40, 40-50, 50-60, 70-80, 80-90, >90 °F ) with days between 60-70 °F as the omitted category.
Figure A4: Using diurnal temperatures
Effects of 24 additional hours at 95 °F relative to 65 °F
1931-2010

Note: See notes to Figure 4. The estimates explore the effects of the proportion of the day in a given 10 °F bin, where diurnal temperatures are linearly interpolated from the daily maximum and daily minimum temperature. The bounds are set at 0 °F and 100 °F. The parameter estimates for time above 100 °F are too imprecisely estimated to draw meaningful conclusions.
Figure A5: Different control variables
Effect of one day with a mean temperature of 95 °F relative to 65 °F
1931-2010

Panel A: No state-by-month trends or division-by-year fixed effects

Panel B: No division-by-year fixed effects

Note: See notes to Figure 4.
Figure A6: Outcome is daily birth rate in levels
Effect of one day with a mean temperature of 95 °F relative to 65 °F
1931-2010

Note: See notes to Figure 4. The mean daily birth rate (population weighted) is 4.7.
Figure A7: Cold temperatures and birth rates
Effect of one day with a mean temperature of 15 °F relative to 65 °F

Panel A: 1931-1970

Panel B: 1971-2010

Note: See notes to Figure 4.
Figure A8: Estimates by Census region
Effect of one day with a mean temperature of 95 °F relative to 65 °F
Years 1931-2010

Panel A.1: Northeast (different Y-axis scale)  Panel A.2: Midwest

Panel B.1: South  Panel B.2: West

Note: See notes to Figure 4.
Note: These are the estimates from equation (1) with a spline in temperature, but with the addition of a 6th order spline in daily specific humidity in the same model. The spline in humidity has knots at 3, 6, 9, 12, 15, and 18 grams of water vapor per kilogram of air (g/kg). Due to humidity data limitations, the humidity sample covers only the 1945-2010 period. Average (population-weighted) daily humidity levels were above 18 g/kg approximately 1.2% of the year.
Figure A10: Cold temperatures and infant health
Effect of one day with a mean temperature of 15 °F relative to 65 °F
1968-2010 (Panels A-C), 1959-2004 (Panel D)

Panel A: Gestation < 37 weeks (x100)  Panel B: Birth weight < 2500g (x100)
Panel C: Child is female (x100)  Panel D: Log of neonatal mortality rate

Note: See notes to Figure 4. Neonatal deaths are of infants within 28 days of birth. The average daily mortality rate is the number of deaths per 100,000 live births in a given month per days in that month. The neonatal mortality estimates span the years 1959 through 2004.
Figure A11: Climate change temperature projections
Hadley CM3 A1F1 model

Note: Estimated using county population estimates in 2000 as weights. The bias-adjusted climate projections (above) factor out the difference between the realized temperatures and model predictions for the 1990-2002 time period.
Figure A12: Climate change temperature projections
Hadley CM3 A1F1 model

Panel A: Change across temperature distribution, bias-adjusted vs. unadjusted

Panel B: Change in days above 90 °F, by calendar month

Note: Estimated using county population estimates in 2000 as weights. The bias-adjusted estimates factor out the difference between the realized temperatures and model predictions for the 1990-2002 time period.
Figure A13: Residential population with air conditioning

Panel A: Changes over time

![Graph showing changes over time in residential population with air conditioning. The x-axis represents years from 1950 to 1990, and the y-axis represents the fraction with air conditioning. Two lines are shown: one for the entire U.S. and another for the South.]

Panel B: 1980

![Map showing the distribution of residential population with air conditioning in 1980. The states are color-coded based on the percentage of the population with air conditioning: 0 – 20.0%, 20.1 – 40.0%, 40.1 – 60.0%, Greater than 60.0%.]

Note: Air conditioning coverage is the fraction of the population in the respective Decennial Census that had at least one air conditioning unit. Panel A linearly interpolates coverage using the 1960, 1970, and 1980 Census and assuming no coverage as of 1955.
Figure A14: Temperature x modifier interaction
Temperature 9 months prior to birth only
1950-2010

Panel A: Air conditioning
Panel B: Completed high school
Panel C: Food Stamp program
Panel D: Abortion access

Note: Y-axes scales vary across panels. These are the estimates from equation (1) with a spline in temperature as a main effect, the modifier as a main effect, and the temperature variables interacted with the modifier in question. We present the modifier interaction estimates here only. The model has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-calendar-month quadratic time trends. We allow for effects in months 8 through 13 as well, though only report month 9 here. We control for fraction of days with precipitation between 0.01 and 0.50 inches, 0.51 and 1.00 inches, and over 1.01 inches in each month. Estimates are weighted by state-year population. Standard errors are clustered at the state level.

See text for a description of the air conditioning variable. We have information on female education levels from decennial censuses between 1940 and 2000 and from the annual American Community Surveys between 2001 and 2010. The data also contain information on state-of-residence. We linearly interpolate our state-year measures of maternal education between the decennial censuses. We focus on females between 18 and 45 with a high school diploma. We construct a state-year measure of access to Food Stamp programs using data from Hoynes and Schanzenbach (2009). The Food Stamp program was first implemented at the county level, starting as early 1961. The last county implemented Food Stamps in 1975. We construct a state-level measure of Food Stamps access by taking a population-weighted average of the counties with a Food Stamp program, where the population weight is fixed at 1960 (Hoynes and Schanzenbach 2009). 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.
Figure B1: Hypothetical example

Fall in conception probability at t=0

Note: This fictitious example illustrates a one time fall in conception probabilities, while holding all other conception probabilities constant. For births, we assume the distribution of gestational lengths is equal to actual gestational lengths in the 2004 Natality Data.