It's Getting Hot in Here: The Effects of Ambient Temperature on Seasonal Birth Rates

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Abstract

Ambient temperature is a potentially important determinant of seasonal birth rates. Existing studies are conflicted on the magnitude and form of the relationship as well as potential mechanisms. Using a novel empirical model, we estimate the effects of temperature on birth rates in the United States at the state-month level between 1931 and 2010. Estimates indicate that extreme heat causes individuals to delay conceptions to later months, causing a dip in birth rates 8-10 months after an extreme heat event, followed by an increase in birth rates 11-12 months later. Conversely, extreme cold has no apparent effect on birth rates. Our temperature estimates are economically meaningful and can explain a substantial portion of the seasonal variation in birth rates. We also observe that the temperature-fertility response function has dampened significantly over time, with the break occurring in the 1970s. We find that access to air conditioning as well as legalized abortion can explain a portion of this dampening. We also explore impacts on birth outcomes. We find that exposure to extreme heat in the third trimester leads to lower birth weight and higher rates of preterm delivery. While individuals can adapt to extreme heat by conceiving in the fall and early winter, this adaptation leads to more children being born in the summer and, as a consequence, exposed to extreme heat during the critical third trimester.

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I. Introduction

There is a strong seasonality in birth rates in the United States, with births peaking at the end of summer. Understanding the factors that influence this seasonality has implications for life course outcomes, health policy, and economic growth. Ambient temperature is a potential explanatory factor, though confounders that vary seasonally (e.g. employment) hinder causal inference.[1] In addition, the underlying mechanisms through which temperature affects birth rates are varied. For example, temperature could influence the timing of births via impacts on fecundity or coital frequency. The relationship could be non-linear, e.g. extreme *heat* could have disparate effects than extreme *cold*. Previous studies are conflicted on the magnitude and form of the relationship as well as the mechanisms (Siever 1985, 1989; Lam and Miron 1991b, 1996; Lam, Miron and Riley, 1994; Buckles and Hungerman, 2013). Our study uses a novel empirical model to investigate the effects of temperature on birth rates in the United States for a period of over 80 years. By accounting for dynamic responses as well as non-linear effects, we provide the most comprehensive analysis of temperature's role in seasonal birth rates.

We analyze the temperature-fertility relationship using state-month data from 1931 through 2010.[2] The birth rate data come from historical documents and machine-readable files produced by National Center for Health Statistics (NCHS). We construct state-month weather data from *daily* station records from the National Climatic Data Center (NCDC). The use of daily weather records allows one to better account for non-linear effects in the temperature-fertility relationship. The focus of our study is on temperature, though we also present estimates for humidity.

Identifying the causal effects of temperature on fertility involves abstracting from usual climatic patterns. Omitted variables could be related to usual seasonal variation in the temperature, including (seasonal) employment, holidays, daylight, and pollution. Furthermore, these seasonal factors could vary across states in a way that is tied to temperature. To overcome this empirical challenge, we include state-by-calendar month fixed effects so that our estimates are identified from plausibly *unexpected* changes in temperature, for a given state and month.[3] Furthermore, we include state-specific trends and year-by-month fixed effects to mitigate potentially spurious correlations between gradual climatic changes and demographic shifts.

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[1] Common hypothesized causes of seasonality include environmental factors (heat/temperature, Photoperiod/luminosity), social factors (Christmas/New Year's holiday), availability of nutrition, preferences for births at certain times of the year, and misinformed reproducer hypothesis (Bronson, 2009; Ellison, Valeggia, and Sherry, 2005; Lam and Miron, 1991a, Meade and Earickson, 2000; Rodgers and Udry, 1988; and Trovado and Odynak, 1993).

[2] These data represent the longest panel for the United States of high-frequency birth rates (to our knowledge). Existing work examines the relationship between temperature and birth seasonality over briefer time periods (Buckles and Hungerman, 2013; Lam and Miron, 1991a, 1991b, 1994, 1996; Lam, Miron, and Riley, 1996; Siever, 1985, 1989).

[3] One well-acknowledged disadvantage of this approach is that behavioral responses to *expected* variation in the distribution of temperatures could be different from behavioral responses to *unusual* variation.

Our empirical model has two innovative features. First, our model accounts for potential non-linear effects of temperature extremes.[4] We model the effects of *daily* temperatures using both a cubic spline and a semi-parametric binned approach. Existing models have imposed much stricter functional form assumptions on the temperature-fertility relationship.[5] Second, we allow for dynamic responses to temperature extremes. For example, extreme temperatures may reduce fecundity and cause individuals to postpone conceptions until the weather improves. We test for impacts over several months preceding the month of conception in order to allow for dynamic responses to temperature shocks. Previous studies (Lam and Miron, 1996; Buckles and Hungerman, 2013) focus on impacts over a limited set of months.

We find that extreme heat around the time of conception is the driving determinant of seasonal birth rates. Moreover, some of the seasonality is due to an inter-temporal shift in conceptions. Specifically, extreme heat *reduces* birth rates 8-10 months later, but causes an *increase* in births 11-12 months later. For example, we find that one additional 95 F day (relative to one 65 F day) reduces the birth rate 9 months later by 0.7%. Conversely, one additional day at 95 F day increases the birth rate 12 months later by 0.1%. Cold temperatures have no discernable effect on the timing of births. These estimates carry economic significance. Using our temperature-fertility estimates, we can predict around half the seasonal variation in birth rates in the United States. We also explore the role of selection by examining impacts on maternal characteristics and birth outcomes. In short, we find that women with better health capital, though potentially lower socioeconomic status, are more likely to engage in strategic adaptation.[6]

Our research can also help guide our ability to adapt to climatic shocks by exploring changes in the temperature-fertility relationship 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 that access to air conditioning can explain a portion, but not all, of this dampening. We examine several other factors that could have led to these changes. To explore the role of nutrition in low-income populations, we exploit variation in the implementation of Food Stamps across states and time. We do not find an effect for Food Stamps. Next, we find that access to abortion also mitigates birth seasonality, though the effect size is only modest compared to air conditioning. This suggests that temperature-driven seasonality in births is partly comprised of women not planning to conceive.

The results from this study have important implications for climate change policies and economic growth.[7] Climatologists predict an increase in extreme weather events,

[4] 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). To the extent that health influences fertility patterns, then accounting for non-linear effects is likely to be important.

[5] For example, Lam and Miron (1996) use a quadratic in monthly average temperature.

[6] Additionally, there could be a link to the "wantedness" of births (Buckles and Hungerman 2013).

[7] Recent contributions have focused on understanding the climate impact on human mortality (e.g. Deschenes and Greenstone 2011, Barreca 2012, Barreca et al 2013).

especially with respect to extreme heat, in the coming century. Quantifying the temperature-fertility relationship is important for evaluating the extent to which climate change might compound (or offset) "below-replacement" birth rates in developed countries.[8] These below-replacement fertility rates pose serious challenges to public finance and economic growth. For example, low fertility rates can lead to funding problems with social insurance programs (e.g. Social Security) (Goss, 2010). We use our estimates and climate-change model predictions to provide the best available estimates on birth rates through the end of the 21st century.[9] Our back-of-the-envelope calculation suggests an economically small (<1%) and statistically insignificant decline in fertility rates by 2070-2099.

The small net effect masks potential important changes in birth seasonality. Increases in extreme heat from climate change during the summer months will shift conceptions to the fall and winter, causing more children to be born the following summer. As such, climate change will expose more children to extreme heat in the third trimester. Both our research here and previous work (Deschenes et al. 2009) show that exposure to extreme heat in the third trimester leads to a statistically significant increase in low birth weight. Thus, climate change is likely to lead to worse birth outcomes, not only from an increase in the frequency of extremely hot days, but also from a change in seasonal birth patterns. The extent to which early-life exposure to extreme heat has lasting consequences, like other health shocks studied, is an open and pressing question for future research.[10]

II. Background on the temperature-fertility relationship

Temperature could directly impact seasonal birth rates through numerous physiological and behavioral channels.[11] Physiologically, temperature may alter fecundity either on the male or the female side. Prior work suggests that 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).[12] Additionally, temperature extremes could

[8] 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.
[9] Specifically, we combine our temperature-fertility estimates with "business as usual" climate change projections from the Hadley CM3 A1F1 model.
[10] Almond and Currie (2011) survey the literature on the fetal origins hypothesis, which posits that early-life health shocks have consequences for lifelong outcomes. The existing evidence provides compelling support for this hypothesis.
[11] We focus on the direct effects, though temperature could indirectly impact outcomes via changes in market equilibriums.
[12] 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).

affect birth seasonality via fetal loss or gestational length (Lam, Miron, and Riley, 1994; Dadvand et al, 2011; Strand, Barnett, and Tong, 2011).[13]

Behaviorally, temperature may influence the timing and/or frequency of coitus. Extreme heat could raise the physiological cost of coitus. Temperature may affect time use and behavior (Zivin Graff and Neidell, 2014), in turn, impacting mixing rates among potential partners.[14] Ambient temperature affects hormone levels, which could impact coital frequency. Importantly, the physiological mechanisms mentioned above could lead to intertemporal substitution of coitus (or conceptions) across months. For example, individuals could time coitus to periods of better fecundity. Individuals may also be attempting to time births in order to avoid being pregnant during the summer heat, either to maximize infant health outcomes or minimize the costs of pregnancy.[15]

Although many studies point to temperature as playing a key role in the observed seasonal pattern of birth, few studies have explored the temperature-fertility relationship using observational data. In order to make the case that extreme heat was behind the seasonality of births, Siever (1985, 1989) correlated changes in seasonality between 1947 and 1980 with the adoption of air conditioning. Using vital statistics data from 1942 through 1988, Lam and Miron (1996) was the first study to rigorously examine the impact of temperature on birth rates. Lam and Miron find that extreme heat leads to a reduction in births rates 9 to 10 months later. However, Lam and Miron's model admittedly relied on strong functional form assumptions and was not well suited to quantifying non-linear effects in daily temperature, something our model addresses. Additionally, Lam and Miron only find significant impacts 9 and 10 months later, while we find effects in other months.

Our work also helps address the relationship between season of birth and life course outcomes. Currie and Schwandt (2013), for example, show a strong seasonality in birth outcomes, even when comparing outcomes within mothers.[16] Buckles and Hungerman (2013) recently explored the role of maternal selection in explaining differences in outcomes across season of birth. They comprehensively document the fact that summer

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[13] 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).

[14] 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.

[15] Using the National Survey of Family Growth, Rodgers and Udry (1988) found that individuals report stopping contraception most often in June and July. If women assume they will conceive right away, these stopping times are consistent with respondent reports of April and May as the best time to have a child and December and January as the worst. Rodgers and Udry hypothesize that due to the mismatch between expected and realized conception month, women have children later than expected, the misinformed reproducer hypothesis.

[16] Currie and Schwandt (2013) hypothesize that seasonality in influenza could be an important factor. Our work shows that exposure to extreme temperatures can help explain some of the seasonality in birth outcomes.

(winter) births are more often to women of higher (lower) socioeconomic status. Buckles and Hungerman also examine potential causes of this seasonality, including temperature. However, they do not present the estimated temperature-fertility relationships, and instead focus on explanatory power. They conclude that weather at the time of birth, as opposed to weather at conception, is a better predictor of birth seasonality. On the contrary, our evidence suggests that weather at conception is the driving force behind seasonal births. We return to this point in the Discussion section.

III. Data

Natality data

Birth counts are available at the state-month level from 1931 through 2010.[17] The data come from three sources. We compiled state-month birth counts from historical Vital Statistics reports for the year 1931-1967.[18] We used machine-readable Natality Files for the years 1968-2004.[19] And, we 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.[20]

We construct state-month birth *rates* by dividing the birth counts by the total estimated population in that state and year. For the years 1931 through 1968, we estimate state-year populations by linearly interpolating between Decennial Censuses (Haines 2004). For the years 1969 through 2010, we use state-year population estimates from the National Cancer Institute (2013). Our outcome of interest is the log of the birth rate, though our results are robust to using birth rates in levels.

The data also permit an analysis of maternal and child characteristics. We have state-month birth counts by race, but these data are only available in the historical Vital Statistics reports starting in 1942.[21] For the years 1968 through 2010, we can test for impacts by the age mother, birth order, and education level of the mother. To test for impacts on fecundity, we also compiled state-month birth counts by sex of the newborn, though these data are only available between 1942 and 1959 and between 1968 and 2010. Starting in 1968, we can also explore impacts on birth outcomes, including birth weight and gestation. We can

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[17] 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.
[18] 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.
[19] 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.
[20] State of residence is the preferred measure since migration could be endogenous to temperature.
[21] 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.

also test for impacts on neonatal mortality rates over the 1959-2004 period using the *Multiple Causes of Death* files.[22]

Weather data

The primary weather data come from the National Climatic Data Center's United States Historical Climatological Network (USHCN). The USHCN have daily station information on minimum temperature, maximum temperature, and precipitation over our sample period (1931-2010). The USHCN data have relatively good geographic coverage across the continental United States during our sample period. For example, there were 966 stations in 1930 and 1,055 stations in 2010.[23]

We construct state-month weather measures from the station-day observations as follows: First, we aggregate the station-day data to the county-month level using inverse distance weights, where distance is measured 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.[24] 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, i.e. 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").[25] The humidity variable has poor coverage prior to 1945, so we control for humidity in one robustness check. Nonetheless, humidity and temperature are naturally correlated, so our temperature estimates incorporate some of the effects of humidity.[26]

Modifier variables

In one set of estimates, we correlate changes in the temperature-fertility relationship with a set of modifier variables, including air conditioning (AC) usage. The AC data were linearly interpolated from the 1960, 1970, and 1980 Censuses. These data include information on state of residence and whether the household had AC.[27] We assume that air conditioning

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[22] 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.

[23] "USHCN stations were chosen using a number of criteria including length of record, percent of missing data, number of station moves and other station changes that may affect data homogeneity, and resulting network spatial coverage." (USCHN)

[24] We linearly interpolate county population between the decennial censuses up until 1968. Starting in 1969, we use county population estimates from SEER.

[25] As discussed in Barreca (2012), specific humidity is a better proxy for health conditions than other measures of humidity (e.g. relative humidity).

[26] 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.

[27] We define "air conditioning" as at least one air conditioning unit or a central air conditioning.

coverage was zero as of 1955. And, we use the growth rate in AC coverage between 1970 and 1980 to project out to 2010, where we cap AC coverage at 100%.

We have information on education levels, poverty rates, and labor supply 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 demographic measures between the decennial censuses. Our modifier analysis focuses on the fraction of the females between 18 and 45 with a high school diploma. Future will work will examine the role of other moderating socioeconomic factors.

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. We plan to explore the modifying effects of birth control in future work.

Climate change predictions

Our climate projections come from the Hadley CM3 model. We use the A1F1 scenario, which assumes no concerted reduction in pollution, often referred to as the "business as usual" scenario. The unit of observation is day by grid point, where the grid points are spaced out every 2.5 degrees latitude and 2.5 degrees longitude, respectively.[28] Variables include minimum temperature, maximum temperature, precipitation, and specific humidity. We aggregate the Hadley data to the county level using inverse distance weights. Then, we aggregate the data up to the state level using county population in 2000 as weights. Finally, we adjust the predictions to account for the fact that the Hadley model predicted warmer weather than actually realized during the earlier years of the model run.

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:

[28] A 2.5 degree change in latitude (longitude) is roughly 150 (111) miles around Chicago and 170 (130) miles around New Orleans.

$$(1)\ Y_{st} = \sum_{k}^{K} \beta^k\ f(TEMP)_{s,t-k} + \gamma\, X_{st} + \ \delta_{sm} + \alpha_t + \pi_{sm} * t + e_{st}$$

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.[29] α is a set of year-by-calendar-month fixed effects that help account for changes in temperature over time that might be spuriously correlated with demographic changes at a national level. δ is a state-by-calendar-month fixed effect so our model is identified from unusual temperatures in a given calendar month. π is a set of state-by-calendar-month quadratic time trends to mitigate potential biases from convergence in outcomes across states and seasons. We cluster the standard errors at the state-level to allow for serial correlation in the errors at the state-level. And, we weight the estimates by the state-year population mitigate statistical noise in the outcome in less-populated states.[30]

The temperature function *f(TEMP)* is designed to account for possible non-linear effects in temperature. We vary the functional form of TEMP in two key ways. First, we use a 6th order polynomial spline in the daily mean temperature, where the nodes are set at 15, 30, 45, 60, 75, and 90 F. Second, we use a binned approach where we control for the fraction of the month with daily mean temperatures <30F, 30-40F, 40-50F, 50-60F, 70-80F, 80-90F, >90F, with the fraction of month with temperatures between 60 and 70F as the omitted category. Our estimates are qualitatively similar across these two specifications. However, we make the spline model our core specification since the standard errors are more precisely estimated. These approaches make significant advances over the previous literature. For example, the most rigorous study to date, Lam and Miron (1996), use a quadratic in monthly average temperature.

In our core model, we allow for effects in months t-18 through t+3. Months t-7, t-8, t-9, and t-10 could affect birth rates in month t via conceptions across children of varied gestational length, fecundity, or fetal losses. We include months t-11 through t-18 to allow for inter-temporal displacement of conceptions. For example, a temperature shock in September of 1950 may cause individuals to postpone conceiving until December of 1950, leading to an increase in the birth rate in July of 1951, or 12 months (t-12) after the initial temperature shock. Months t-8 through t-0 could affect birth rates in month t via gestational length or fetal losses.[31] Months t+1 through t+3 serve as a placebo check since these temperatures were realized after delivery. Note that this modeling approach is a big improvement over previous studies. The model in Buckles and Hungerman (2013), for example, includes

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[29] 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. In general, we find that days with more than 1.01 inch of rain in month t-9 lead to a sizable decline in birth rates at time t. These results are available upon request.

[30] We linearly interpolate the state-year population between decennial censuses up until 1968. Starting in 1969, we use state-year population estimates from SEER.

[31] In fact, we find evidence that extreme heat reduces gestational length.

exposure 9 months and 12 months from birth. Lam and Miron (1996) focus on months 9 and 10, though they footnote finding insignificant results in months 7, 8, and 11.

As a robustness check, we also use diurnal temperatures, in place of daily mean temperatures. This specification accounts for the 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.[32] We also include humidity in one specification. To our knowledge, we are the first to estimate the impact of humidity or diurnal temperatures on birth rates.

We also estimate a variant of equation (1) at 10-year sample intervals in order to document changes in the temperature-fertility relationship over time. Given smaller sample sizes, we omit the state-by-calendar month trends from that specification. This analysis shows a significant dampening in the temperature-fertility response function starting in the 190s.

A key contribution of our research is to explain the dampening of the temperature-fertility relationship over time. We focus on quantifying the role of various potential "modifiers", including: air conditioning, female education levels, nutrition, and abortion. We test these hypotheses by interacting our temperature variables with a measure of a particular modifier (e.g. air conditioning). Specifically, we estimate:

$$(2)\ \ Y_{st} = \sum_{k}^{K} \beta^k\ f(TEMP)_{s,t-k} + \sum_{k}^{K} \varphi^k\ MOD_{sy}\ x\ f(TEMP)_{s,t-k} + \mu\ MOD_{sy}$$
$$+ \gamma\ X_{st} + \ \delta_{sm} + \alpha_t + \pi_{sm} * t + \textstyle\sum_k^K p^k\ f(TEMP)_{s,t-k} * t + e_{st}\ ,$$

where MOD is some measure of state-year coverage of the modifier variable (e.g. air conditioning). Since the variation in the modifier is potentially endogenous, we also control for the main effect of the modifier variable to mitigate omitted variables bias. That is, we assume that the correlation between the modifier and any omitted variable is independent of temperature throughout the year. We also control for the interaction between the temperature variables and a time trend (p^k) to mitigate concerns that the modifier is correlated with a general reduction in susceptibility to temperature extremes. In the interest of conserving journal space, we present the φ coefficients on the modifier-temperature interaction only. Also, we use a more parsimonious set of lags and only include exposure in months t-8 through t-12. All other controls are the same as equation (1).

Note that the modifier variables, in some cases, are interpolated between decades (see Data section). To the extent the measurement error 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.

[32] We linearly interpolate the fraction of the day in a given temperature range using the maximum and minimum temperature for a given station-day.

V. Results

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, implying that temperature and birth rates tend to be positively correlated across regions on average. However, this positive relationship cannot be used to infer causal effects since many other factors, including poverty rates, are also correlated with region. These omitted variables highlight the appropriateness of using within-state changes in temperature to identify causal impacts.

Seasonality in birth rates varies considerably across region. Figure 1 Panel A presents the mean of the log daily birth rate, by census region, over our sample period (1931-2010). In every region, the birth rates peak in September suggesting that individuals are more likely to conceive between October and January. But, the seasonality is greatest in the South. For example, September birth rates are approximately 15% higher than May birth rates. The differences in seasonality across regions also suggest that temperature plays a role in the timing of births. Again, however, omitted variables hinder our ability to infer causality. There could be other seasonal factors, like demand for agricultural labor or Mardi Gras celebrations, which could account for different birth seasonality across states. Note that our empirical model mitigates this type of concern by including state-by-calendar-month fixed effects.

Panel B of Figure 1 indicates that 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, respectively. During the 1931-1949 period and the 1950-1979 period, the daily birth rate was approximately 10% higher in September than in April. However, the difference between the April and September daily birth rates was closer to 5% during the 1980-2010 period. This observation suggests that the temperature-fertility relationship dampened significantly towards the end of the 20^{th} century. We quantify changes in the temperature-fertility relationship, as well potential causes of this dampening, in a regression framework.

Core results

We first estimate a model where *f(TEMP)* in equation (1) is modeled as a 6^{th}-order cubic spline. We allow for effects from 18 months prior to birth through 3 months after birth. We include months as late as t-18 to allow for dynamic responses of up to a 9 months. As a starting point, we estimate the model for our entire sample period (1931-2010). Below, we allow the temperature-fertility relationship to vary by 10-year periods.

Figure 2 presents the temperature-fertility response function for four key exposure months. Specifically, we illustrate the estimates for months t-9, t-10, t-11, t-12, though the model controls for exposure between months t-18 and t+3. There are three important lessons in Figure 2. First, we observe an economically large and statistically significant decrease in births from exposure to high temperatures in months t-9 and t-10. For example, one additional day at 95 F reduces the birth rate 9 months later by 0.7% and 10 months later by 0.4%.[33] Second, high temperatures lead to a modest and statistically significant *increase* in births 11 to 12 months later. For example, one additional day at 95 F increases birth rates 12 months later by 0.1%. Third, low temperatures have little effect on birth rates. At each month of exposure, we can rule out effect sizes of +/- 0.1% from exposure to one additional 35 F day. In combination, these estimates suggest that hot weather alters the conception timing in ways consistent with intertemporal substitution, potentially driven by changes in fecundity or coital frequency as described above.

Figure 3 explores the effects across a larger set of exposure months. In the interest of space, we focus on the marginal effects of one 95 F day (Panel A) and one 35 F day (Panel B). The estimated effect sizes at these temperatures and relevant months are, by construction, identical to those in Figure 2. Exposure to hot weather in months t-9 and t-10 causes a large decrease in birth rates 9 and 10 months later, but a modest increase in births 11 and 12 months later (Panel A). Figure 3 indicates that exposure to one 95 F day also results in a statistically significant decrease in births 8 months later, though the effect size is relatively small (0.1%). Other than months t-8 through t-12, exposure to heat appears to have little effect on later birth rates. Importantly, we find that temperatures in month t+1 through month t+3, or the few months *after* birth, have little relation with birth rates in month t. As such, our empirical model appears to be free of bias from spurious time trends.

In sum, our estimates suggest that hot temperatures impact fertility decisions, but cold temperatures do not. Also, the estimates suggest an intertemporal shift in the timing of conceptions. That is, the birth rate falls 8 to 10 months after exposure, but then increases 11 to 12 months later. Whether the intertemporal substitution is due to changes in fecundity or coital frequency is not readily apparent. We return to the challenge of distinguishing mechanisms below.

Effects over time

We explore changes in the temperature-fertility relationship over time. In the interest of space, Figure 4 presents changes in the marginal effects of 95 F days in months t-9 (Panel A) and t-12 (Panel B) only. Also, given the shorter time periods, we omit the state-month trends from the model to improve precision.[34] As Panel A illustrates, the marginal effect of each 95 F day is relatively stable between the 1930s and 1960s. For example, exposure to

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[33] 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* temperature in months 9 and 10 on birth rates, but the model is estimated separately by state and race. (Further, they model temperature as quadratic.) 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).

[34] The estimates are qualitatively similar, though more imprecise, when we include the trends.

one additional 95 F day causes the birth rate 9 months later to fall by about 1% in the periods before 1970. However, the effect sizes are cut in half by the 1980s. One additional 95 F day causes the birth rate 9 months later to fall by less than 0.5% in the 1980s.

Conversely, the magnitude of the dynamic response appears to have dampened only slightly over time. Panel B shows that each additional 95 F day increases the birth rate 12 months later by approximately 0.3% in the 1950s and about 0.2% in the 1980s. Interestingly, there is a stark dip in the 1970s, possibly driven by unique socioeconomic conditions of the time (e.g. energy crises).

In sum, the results in Figure 4 suggest that there was a structural break in the temperature-fertility relationship in the 1970s. Figure 5 revisits the effects of each 95 F day by exposure month during the 1931-1970 and 1971-2010 periods. As might be expected given our findings above, the effect sizes are larger in magnitude in the earlier period (Panel A). However, splitting up the sample reveals a couple important findings. First, there is a statistically significant *increase* in births from heat exposure in the month of birth. This fact suggests that extreme heat may induce labor and reduce gestational length. We revisit this possibility below using detailed natality data from the 1968-2010 period. Second, extreme heat may have a longer lasting effect on birth rates in the latter period. We observe modest positive effects on birth rates out as far as month t-18.

Seasonal predictions

Next, we investigate the economic magnitude of our estimates by exploring the degree to which they can explain the observed seasonal relationships. For this analysis, we rely on our Figure 4 estimates, which break the sample into the 1931-1970 and 1971-2010 time periods. That is, we take the estimates and apply them to the average distribution of temperatures over each time period. In the earlier period, the predicted values follow a nearly identical pattern, with births at a trough in April and a peak in September. The model does overestimate birth rates in February and March. That said, the model still explains approximately over half of the variation ($R^2 = 0.526$) when correlating the predicted points to the actual points in Figure 4. In the later period, the predicted values also match the actual seasonality, explaining close to half of the variation ($R^2 = 0.464$). However, in the later period, the model overestimate births in January, February, and March.[35] Nonetheless, we cannot reject the possibility that temperature is the single most influential factor of seasonal birth rates.

Results by race

We begin our exploration of potential mechanisms by exploring impacts by race (Figure 7).[36] We divide our sample up into pre- and post- 1970 time periods. Due to data

[35] When we restrict our model to months t-8 through t-13, the fit is remarkably good.

[36] For this analysis, we must restrict our sample to the 1942-2010 since state by month by race birth counts are not available prior to 1942. Also, we must focus on non-whites because data are only available by white and non-white until 1968.

limitations, the by-race analysis begins in 1942. In short, the effect sizes are greater in magnitude for non-whites. For example, each additional 95 F day reduces birth rates 9 months later by 15% for non-whites (Panel A.2) compared to 10% for whites (Panel A.1) in the 1942-2010 period. This fact suggests that whites may have been better at adapting to climate shocks, possibly via differences in income or wealth.[37]

These racial differences, at least in absolute terms, declined considerably over time. In the 1971-2010 period, each additional 95 F day reduces birth rates 9 months later by 4% for non-whites (Panel B.2) compared to 3% for whites (Panel B.1). Also, exposure to hot days leads to a statistically significant increase in non-white births in the month of birth, suggesting impacts on gestational length. The effect size is also modest and positive for whites, though not statistically significant.

Maternal characteristics

To further explore selection effects, we turn to the detailed Natality data and the post-1968 period. Figure 8 presents the marginal effect of one additional 95 F on various maternal characteristics. In short, we find that exposure to extreme heat is more likely to impact women with markers of low socioeconomic status. Specifically, extreme heat leads to a large and statistically significant 1.0 percentage point decline 9 months later in the probability that the mother has less than a high school education (Panel A). Additionally, there is an increase in the probability of less than high school 12 months on, though the effects are not statistically significant. This suggests that women of low socioeconomic status are more likely to shift conception months.

There is also a large decline 9 months to birth in the probability that the father's age is missing from the birth certificate, a proxy for lack of paternal support (Panel B). However, there is no observable increase in father's age missing 12 months from birth. We observe a statistically significant decline in the probability of first births in month t-10 (Panel C). Conversely, we do not observe any effect on the probability of a teenage birth in months 8, 9, or 10 (Panel D). Additional stratification by age groups reveals that temperature shocks affect women of all ages (see Appendix). Thus, temperature-driven variation in births cannot explain the seasonality in teenage births (Buckles and Hungerman 2013).

Birth outcomes

We next investigate the relationship between extreme heat and two important birth outcomes: birth weight and gestational length. This analysis serves a few purposes. First, like with maternal characteristics, we can test for selection effects by examining outcomes 9 or more months after an extreme heat event. Second, we can test for fetal losses in the early months of pregnancy or about 7 to 8 months before birth. Third, we can investigate whether parents are optimally timing births in terms of infant health.

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[37] One potential explanation for these racial differences is that non-whites are more likely to live in the South. And, humidity levels vary more with temperature than other places. We find that controlling for humidity somewhat mitigates the differences across races.

In terms of selection, we find evidence that extreme heat is causing healthier women to delay conceptions. Specifically, we observe an *increase* in the probability of low birth weight (Panel B) from exposure to 95 F days in months t-9 and t-10, though only exposure in month t-10 is statistically significant. A similar pattern is observed for preterm delivery (Panel D). We also observe lower probability of low birth weight in months t-11 and t-12, though not statistically significant, which is consistent with delayed conceptions among healthier women. The effects on premature delivery are small and statistically significant in months t-11 and t-12.

Consistent with fetal losses to less healthy mothers, we observe better birth outcomes from exposure to extreme heat in month t-8. For example, each 95 F day leads to statistically significant decrease in the probability of low birth weight of 0.5 percentage points (Panel B) and a 0.5 percentage point decrease in preterm delivery (Panel D). This is suggestive of fetal losses potentially driving the observed decline in birth rates in month t-8.

With regards to impacts on infant health, we do observe that exposure to temperature extremes in the month of birth leads to lower birth weight and shorter gestational length. For example, each additional 95 F day in the month of birth causes birth weight to fall by 10 grams (Panel A) and the probability of low birth weight to increase by 0.3 percentage points (Panel B). There is decrease in gestational length of just under 0.05 weeks, or about 0.3 days (Panel C). These estimates suggest that exposure to extreme heat around the time of birth is sub-optimal for infant health.

In Appendix Figure A5, we also investigate the relationship between temperature and neonatal mortality. We find that exposure to extreme heat in the month of birth causes an increase in neonatal mortality, statistically significant at the 10% level. These estimates further corroborate the findings that exposure to extreme heat around the time of birth is sub-optimal for infant health. We discuss the implications of this and our other birth outcome findings in the context of dynamic fertility responses below.

Impacts on sex ratio

To further investigate the fecundity channel, we look at the impacts on the sex ratio from exposure to extreme heat during the early months of pregnancy. Recent research provides compelling evidence that female fetuses are more resilient to in utero health shocks (Trivers Willard, 1973; Sanders and Stoecker, 2011). If extreme heat affects fecundity, we might expect an increase in the proportion of births that are female 7 or 8 months later. One limitation of this analysis is that the changes in the sex ratio might not be a good proxy for fecundity at implantation, or around 9 months prior to birth.

Like above, we break our sample into the pre-1970 and post-1970 periods. However, birth counts by gender are not available prior to 1942 or between 1960 and 1967. Thus, the earlier period has fewer observations than above. Possibly owing to smaller sample size, the estimates appear to resemble random noise and the standard errors are quite large in the earlier period. As Figure 10 Panel A illustrates, we cannot reject the possibility that each day at 95 F (relative to 65 F) changes the fraction female by +/- 1 percentage point.

In the later period, while the estimates are also somewhat noisy, we do find evidence consistent with the fetal loss mechanism. Specifically, exposure to extreme heat leads to a statistically significant increase in the fraction of female births 7 months later, or about two months into pregnancy. The magnitude is quite large: a 0.5 percentage point increase from each day at 95 F. This suggests that exposure to extreme heat in the first trimester can lead to fetal losses. As an important aside, exposure to extreme cold leads to a statistically significant increase in female births 8 months later (results not reported), also suggestive of fetal losses. These estimates suggest that optimal birth timing is one that avoids any temperature extremes in the early stages. However, we find a statistically significant decrease in the probability of female birth in month 9. This suggests that extreme heat reduces the chances that less healthy women conceive, which contradicts our findings in the birth outcomes analyses (Figure 9).

Of note, we observe a statistically significant decrease in month t-0 and an increase in the fraction female one month *after* birth. While potentially concerning in isolation, the number of parameters in the model suggests that the occasional parameter will be statistically significant due to random statistical disturbances.

Robustness checks

We test the robustness of our results to different model specifications. We estimate the effects of exposure to a temperature in one of nine 10 F bins (<30, 30-40, 40-50, 50-60, 70-80, 80-90, >90 F). Appendix Figure A1 reports the marginal effects of one additional day above 90 F. 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.[38] The effect sizes are comparable when using diurnal temperatures (Figure A2).

We present the marginal effects of exposure to high temperatures and high humidity levels in Appendix Figure A3.[39] 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 to humidity, one “high humidity” day at 19 g/kg[40] leads to 0.4% decrease in births 9 and 10 months later in the earlier time period. Low humidity levels (not reported) are not a meaningful predictor of birth rates.

We test the robustness to dropping both the state-by-month calendar trends and state-month time trends (Figure A4), dropping the state-month time trends only (Figure A5),

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[38] We linearly interpolate diurnal temperature using the daily minimum and maximum temperatures.
[39] Specifically, we control for daily specific humidity as a 6th order polynomial spline. More details about specific humidity can be found in Barreca (2012).
[40] g/kg = grams of water vapor per kilogram of air. The average county experiences 3 days per year above 18 g/kg.

using state-month linear trends in place of quadratic trends (Figure A6), and with the outcome in levels (Figure A7). We infer conception month using gestational length in the natality data (Figure A8). The estimated relationships are qualitatively similar, though the estimates fail to pass the placebo test for months t+1 through t+3 when we omit the trends from the earlier period. Stratifying the samples by region produces estimates that are similar, except imprecisely estimated in some cases (not reported).

Modifiers of the temperature-fertility relationship

As documented in Figure 4, there was a substantial decline in the temperature-fertility relationship starting in the 1970s. Here, we explore some potential explanations for this decline. Specifically, we focus on the role of air conditioning, educational levels of women, nutritional intake via Food Stamps, and access to legal abortions.

We estimate equation (2) where we interact the temperature variables with each modifier variable. Here, we restrict our analysis to the 1950-2010 period to avoid confounding with any factors related to World War II. Figure 11 presents the estimates, from one single model, of the marginal effects of each modifier. In the interest of space, we present the effects of one additional 95 F day on births 9 months later.

We find that air conditioning and access to abortion both mitigated the temperature-fertility response function. For example, at zero coverage across all the modifiers, each additional day at 95 F reduces the birth rate by approximately 0.015 log point (not reported). 100% air conditioning coverage reduces the marginal effect by 0.07 log points, or by about 50% of the original magnitude.[41] The estimate is statistically significant at conventional levels. The effect size for Food Stamps is small and statistically insignificant. The estimates on educational attainment are too noisy to infer meaningful conclusions.

The estimated effect of abortion access is also statistically significant, but smaller in economic magnitude. The response function is dampened by only 0.003 log points, or about 20%. The abortion access finding suggests that high temperatures affect fertility behaviors of women who are not intending to conceive.

VI. Discussion

Possible mechanisms

We find that weather conditions around the time of conception are a strong predictor of seasonal birth rates. Specifically, we observe that extreme heat leads to decline in birth rates 8-10 months later. However, the decline in birth rates is followed by an increase in birth rates 11-12 months later. These different signs suggest an intertemporal shift due to

[41] The marginal effect of air conditioning is 0.7 log points at 95 F; at zero air conditioning coverage, each additional day at 95 F reduces the birth rate by approximately 1.5%.

conditions around the time of conceptions. However, differentiating between physiological and behavioral mechanisms is difficult.

On the physiological side, we observe that birth outcomes improve 7-8 months later from exposure to extreme heat. Coupled with the observed increase in the proportion of female births, this suggests that losses among less healthy fetuses can potentially explain the modest decline in births at month 8. To the extent the women experiencing fetal losses attempt to conceive in latter months, then this could explain the increase in births at months 11 and 12. Furthermore, fetal losses in the early stage of pregnancy may be indicative of lower fecundity at implementation, which would also be consistent with a reduction in births at month 9 and 10, and an increase in births at month 11 and 12. We cannot rule out the possibility, however, that the mechanism is through impacts on paternal health (e.g. sperm motility).

On the behavioral side, extreme heat could reduce coital frequency and, consequently, birth rates 8-10 months later. For women who intend to conceive, reductions in coital frequency during the critical ovulation period would raise the gains to increasing coital frequency in a subsequent ovulation period, which would usually fall one month later. However, for women who do not intend to conceive, there would be gains to increasing coital frequency on a subsequent day *within* a menstrual cycle.[42] Thus, from a behavioral angle, the increase in birth 11 or 12 months later would be more likely driven by women intending to conceive. Indeed, we observe better birth outcomes 11-12 months after exposure to extreme heat, suggestive of a selection effect by healthier women who are plausibly the type who are intending to conceive. That said, the modest sized moderating effect of access to legal abortion (Figure 11) suggests that extreme heat influences birth rates of women who are not intending to conceive, though we cannot differentiate between the coital frequency or fecundity mechanisms for this group of women.

Our reading of the evidence conflicts with one of the conclusions drawn by Buckles and Hungerman (2013) (hereafter BH). Specifically, BH suggest that *expected* weather at birth is a stronger predictor of seasonal birth rates than weather at the time of conception. 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 then show that weather 12 months prior to birth is a stronger predictor of seasonal birth rate than weather 9 months prior.[43] However, if parents were (rationally) looking to avoid harmful temperatures around the time of birth, we would expect a decrease in births 12 months after a harmful heat spell, whereas we find the opposite effect. That said, our model is estimated from unusual variation in the temperature. While our model can explain substantial portion of the seasonal variation in birth rates, some of the remaining variation may still be driven by expected weather

[42] A reduction in conceptions among women not intending to conceive could increase conceptions in subsequent months by increasing the pool of "susceptible" or non-pregnant women.
[43] Their model does account for some non-linear effects in temperature, though not to same degree as our model. Buckles and Hungerman's controls include average minimum temperature, average maximum temperature, days above 90 F, and degree departure from normal temperature.

conditions and a mechanism consistent with what BH propose. However, testing such a claim is infeasible given the data at hand.

Implications for climate change

The Hadley CM3 model predicts 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.[44] In short, there is likely to be at least 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 estimated from Figure 4 panel B, we project that *annual* birth rates will fall by less than 1% (see Appendix Table A1). Furthermore, the projected decline is not statistically significant.

The estimated effect on annual birth rates masks important changes in birth seasonality. Not surprisingly, as Figure 12 Panel A illustrates, the increase in days above 90 F disproportionately fall during the summer months. For example, the Hadley model predicts there will be 10 more days above 90 F during August (on average). Our estimates suggest that this increase in summer temperatures will cause individuals to postpone conceptions until the fall and early winter. As a result, there will be more births in the subsequent summer. Figure 12 Panel B quantifies the magnitude of the effect on seasonal birth rates. There will be approximately 4% more births in August and 4% fewer births in April, for example. As a consequence, more children will be exposed to extreme heat during the third trimester. Our own results as well as work by Deschenes et al (2007) suggest that this shift will increase the frequency of both low birth weight and preterm births.

Our AC estimates suggest that air conditioning could help to 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.

VII. Conclusion

Our estimates suggest that exposure to extreme heat is possibly the singular most important determinant of seasonal birth rates in the United States. While temperature is an important driver of birth rates in the United States, cross-country differences in seasonality suggest that temperature may not be universally important. For example, although close

[44] We use the 1990-2002 time period as the baseline since the climate model data begin in 1990. Thus, we can only adjust for potential biases in the climate-change predictions for this time period. We do not have access to data outside this time frame.

geographically and culturally to the United States, Canada's seasonality patterns are different, with births peaking in both May and September (Rosenberg, 1966; Trovato, F. and D. Odynak. 1993; Cummings, 2012). Birth rates are generally highest in the spring and early summer in Western Europe (Lam and Miron 1996). Therefore, other factors, like photoperiod, might be more important than temperature elsewhere.[45] Quantifying the temperature-fertility relationships in different countries and other historical settings is an important avenue of future research.

[45] Other hypothesized causes of cross-country differences in seasonality include environmental factors (photoperiod/luminosity), social factors (holiday seasons), availability of nutrition, preferences for births at certain times of the year, and misinformed reproducer hypothesis (Bronson, 2009; Ellison, Valeggia, and Sherry, 2005; Lam and Miron, 1991a, Meade and Earickson, 2000; Rodgers and Udry, 1988; and Trovado and Odynak, 1993). Note that social and environmental causes could reinforce each other, making it difficult to disentangle their respective effects.

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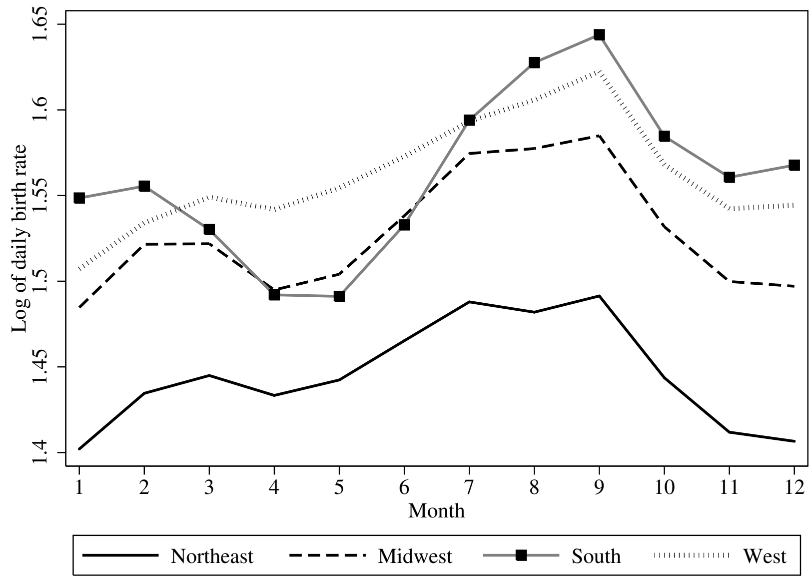
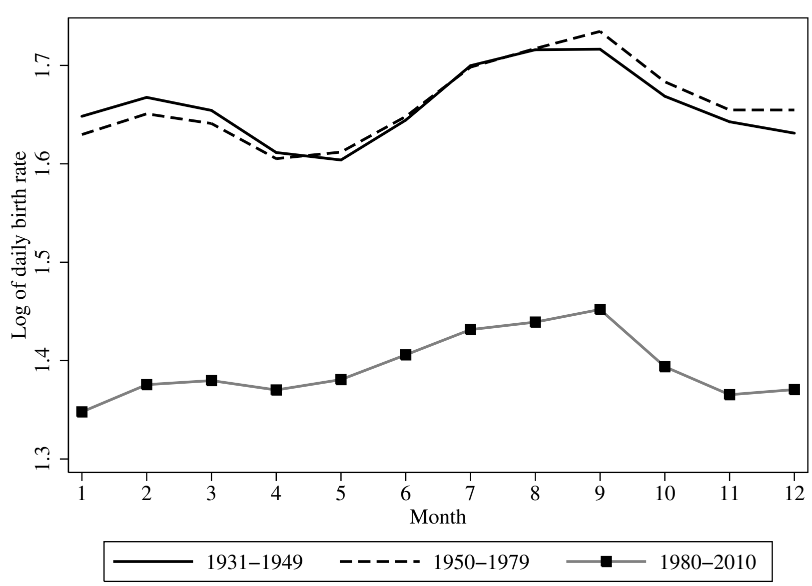
Figure 1: Daily birth rate per 100,000 residents by month

Panel A: Differences by Census region, 1931-2010

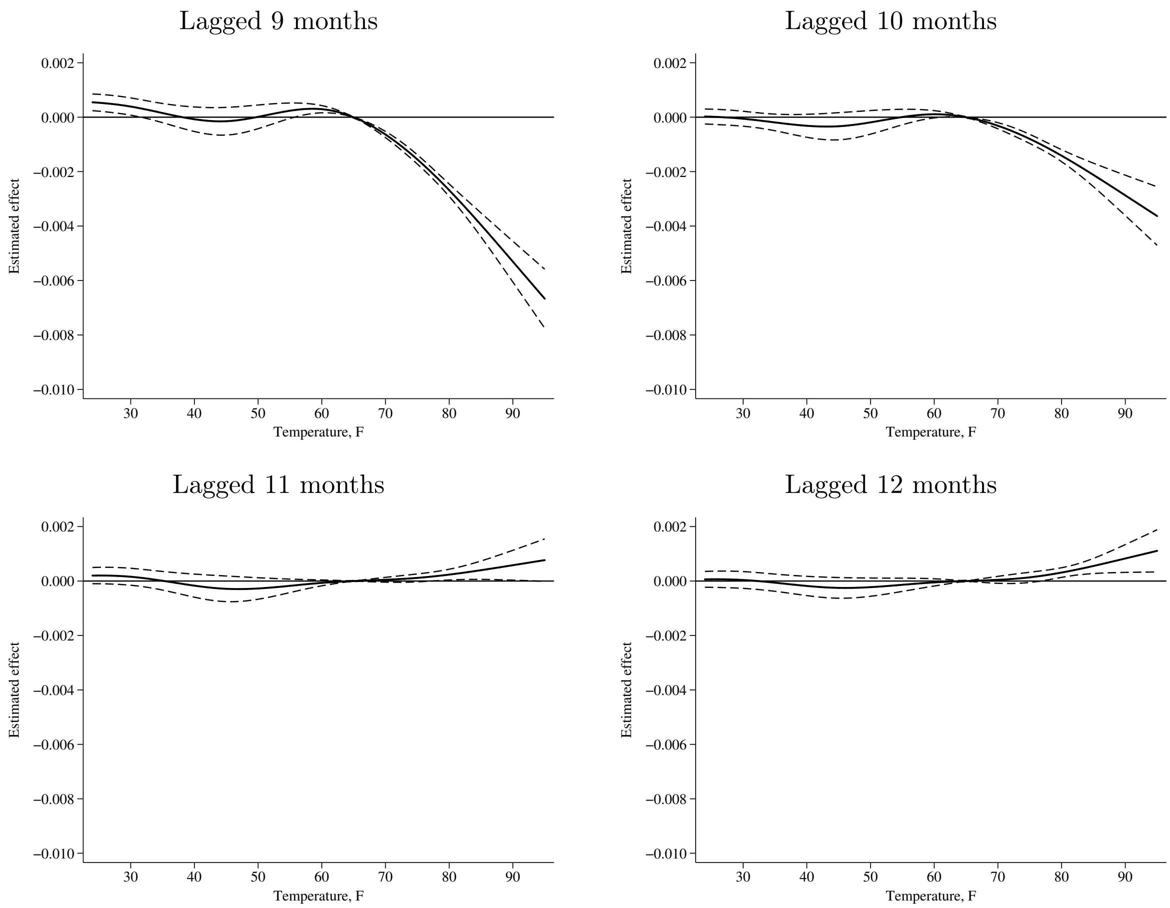


Panel B: Differences by time period



Note: Estimates using state-year populations as weights.

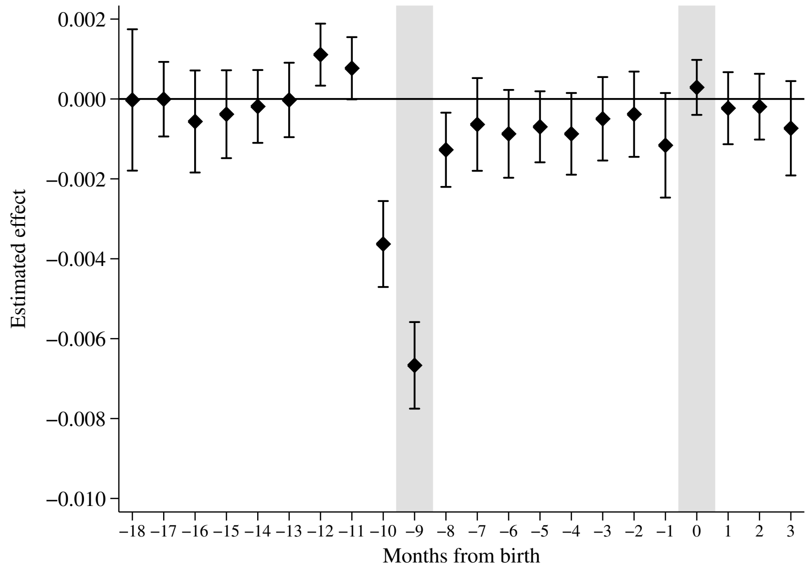
Figure 2: Marginal effect on the montly birth rate of a temperature change in a given month
1931-2010 period



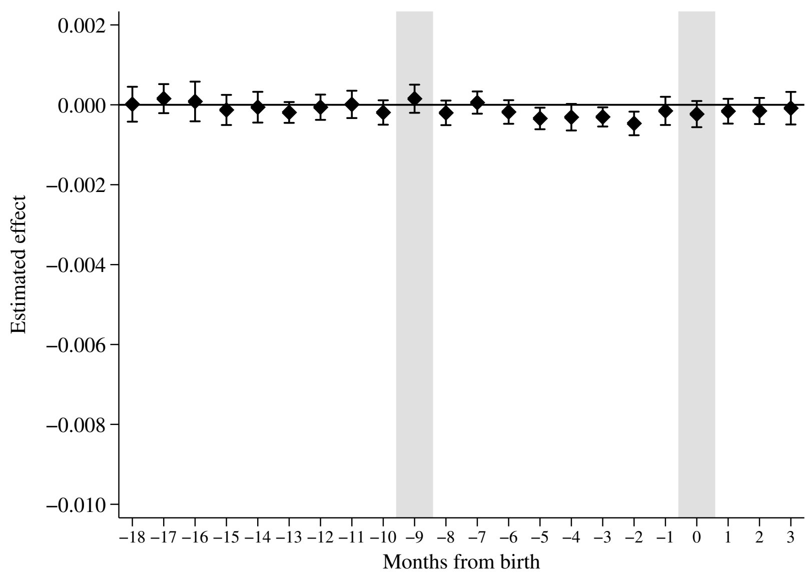
Note: The spline estimates are the solid line and the dashed line represent two standard errors around the point estimates. The estimates can be interpreted as the impact, in log points, of one additional day at a given temperature relative to 65 °F on the monthly birth rate. The spline estimates have knots at 15, 30, 45, 60, 75, 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, and state-by-calendar month quadratic time trends. 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 exposure in months t-18 through t+3, though we only report the estimates on months t-12 through t-9 here. Estimates are weighted by state-year population. Standard errors are clustered at the state-level.

Figure 3: Marginal effect of a change in one day's temperature
by months-from-birth and by time period

Panel A: Effects of increasing temperature from 65 to 95 °F



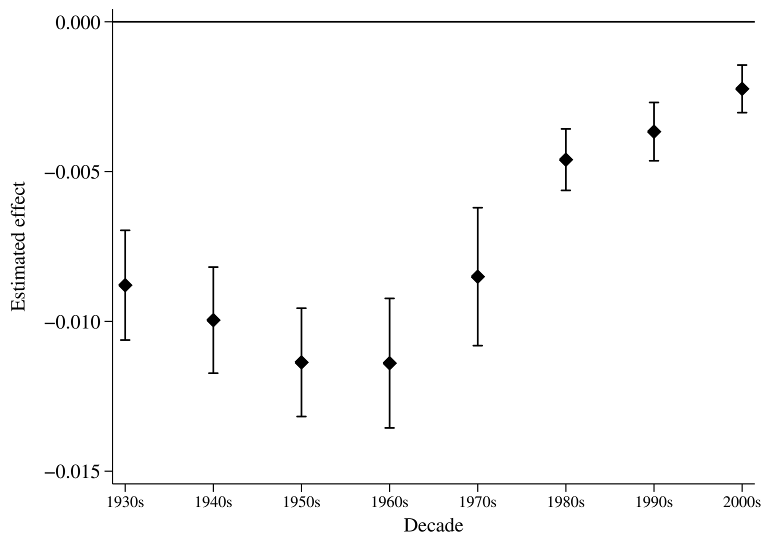
Panel B: Effects of decreasing temperature from 65 to 35 °F



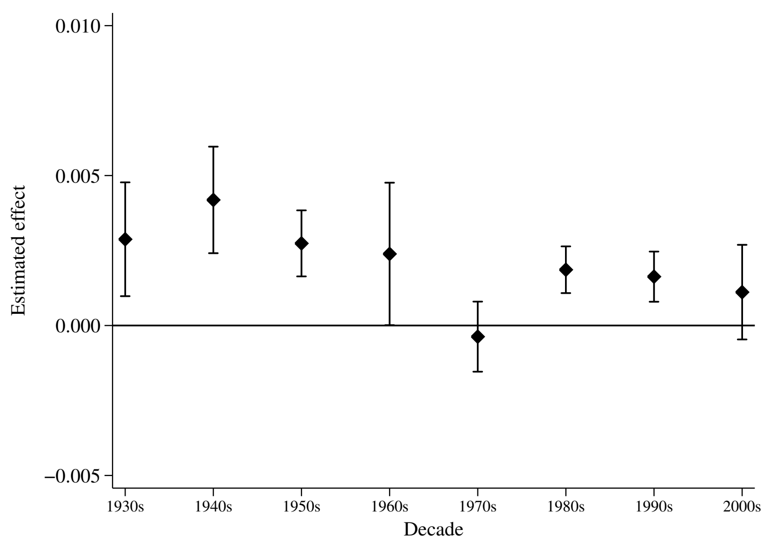
Note: The brackets represent +/- two standard errors. The gray shading highlights both month t and month t-9. These are the estimates from equation (1) with a spline in temperature. The spline estimates have knots at 15, 30, 45, 60, 75, and 90 °F . The model has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-calendar-month quadratic time trends. 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. Estimates are weighted by state-year population. Standard errors are clustered at the state level.

Figure 4: Effects over time
Marginal effects of increasing temperature from 65 to 95 °F effect
By month to birth

Panel A: 9 months to birth



Panel B: 12 months to birth

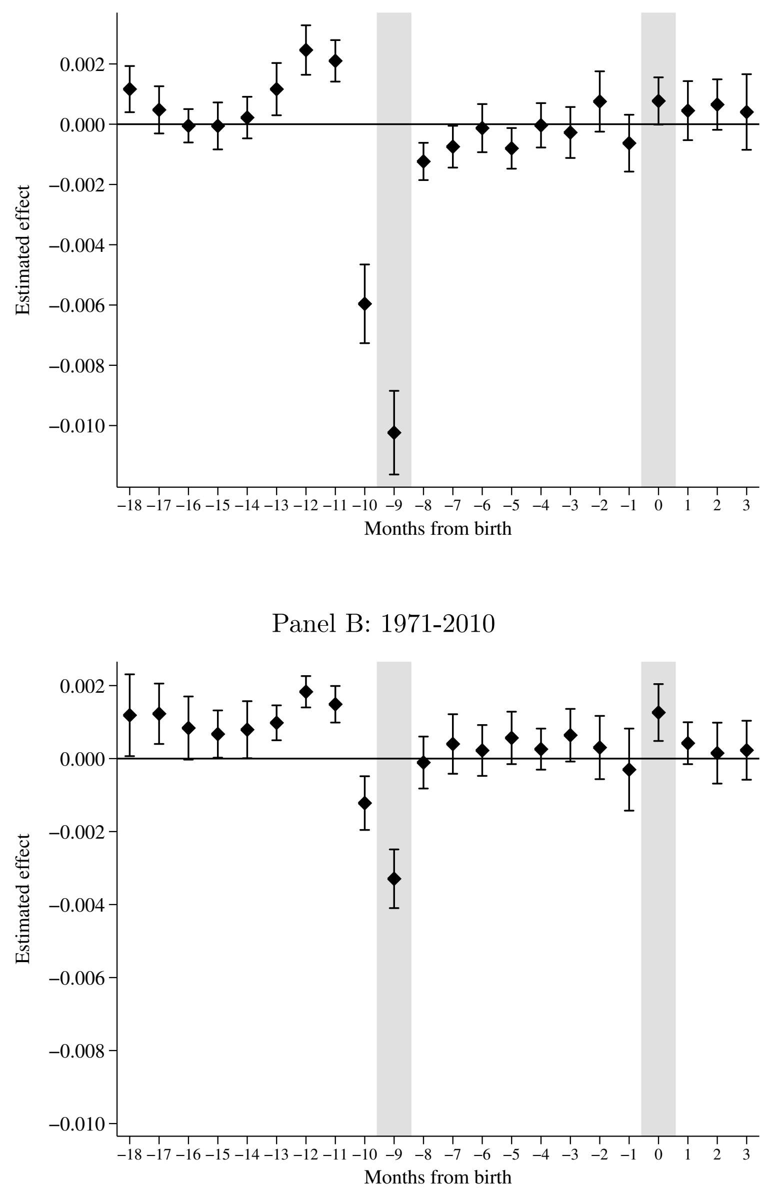


Note: The brackets represent +/- two standard errors. These are the estimates from equation (1) with a spline in temperature. The model has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-calendar-month linear time trends. We control for temperatures in months t-8 through t-13 as well, though only report month t-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 5: Two sample periods
Marginal effect of one additional 95 °F day
By month of exposure

Panel A: 1931-1970

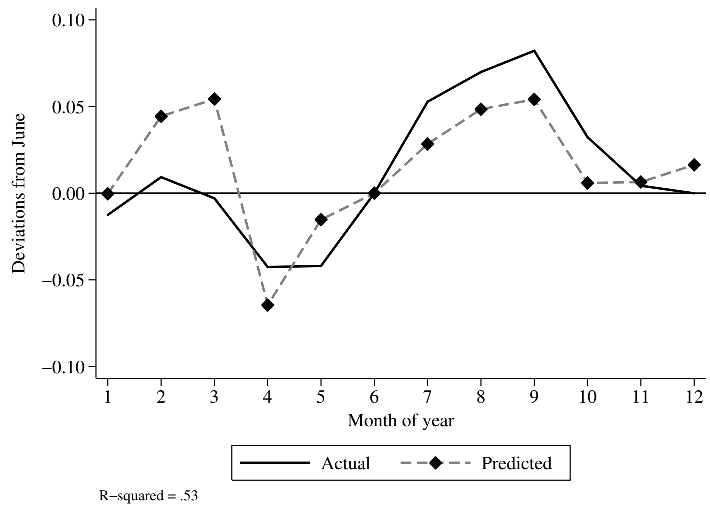
Panel B: 1971-2010



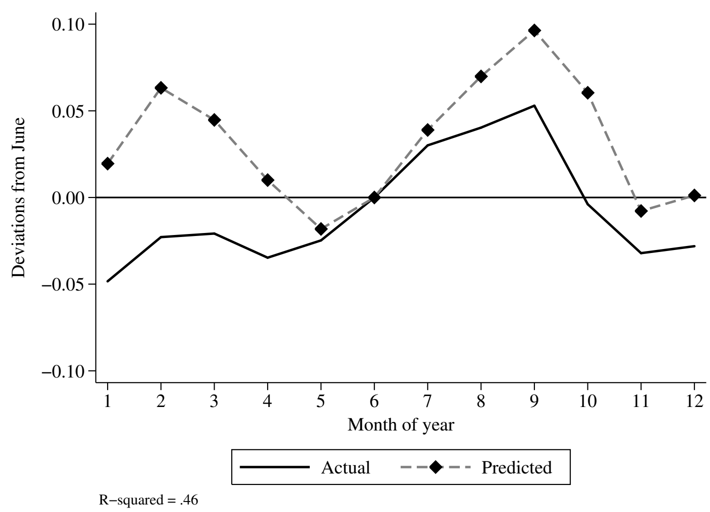
Note: See notes to Figure 3.

Figure 6: Seasonal predictions
Outcome: Log of the birth rate
By time period

Panel A: Years 1931-1970



Panel B: Years 1971-2010

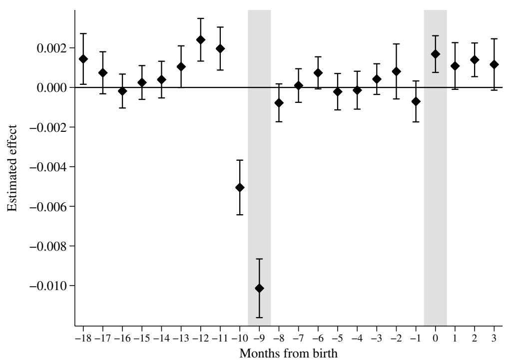


Note: The predictions are based on the estimates in Figure 5. We use only the temperature estimates to make these predictions, and ignore rainfall and all other controls. We recenter both the observed and predicted values around June so the values should be interpreted as deviations, in log points, from June.

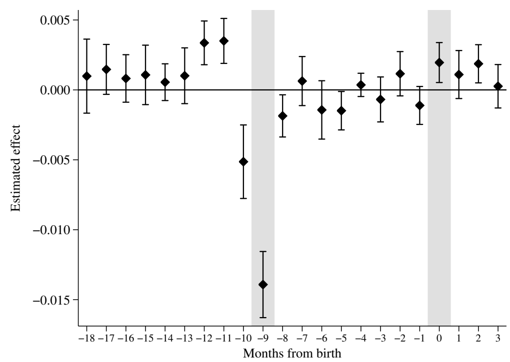
Figure 7: Estimates by race
by months-from-birth
Years 1942-2010

Panel A: 1942-1970

Panel A.1: Whites

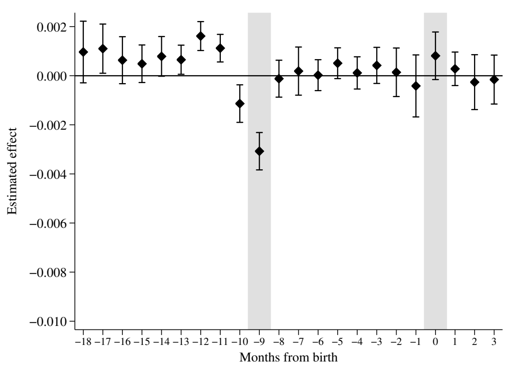


Panel A.2: Non-whites*

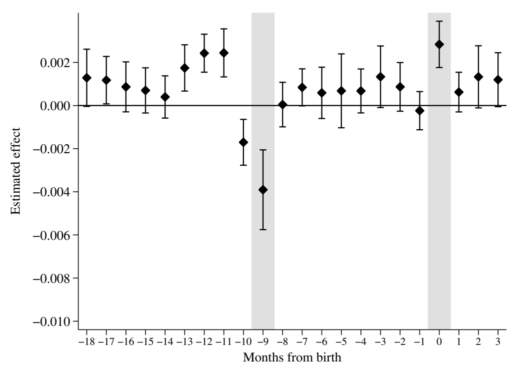


Panel B: 1971-2010

Panel B.1: Whites

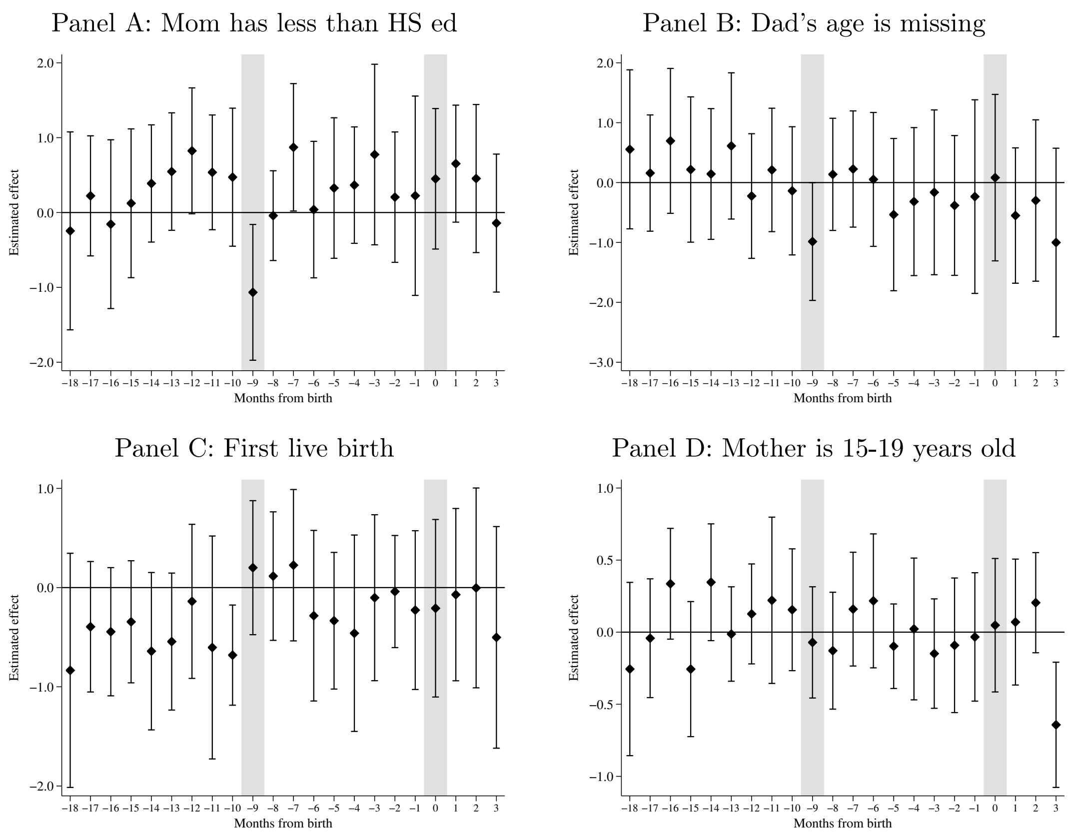


Panel B.2: Non-whites



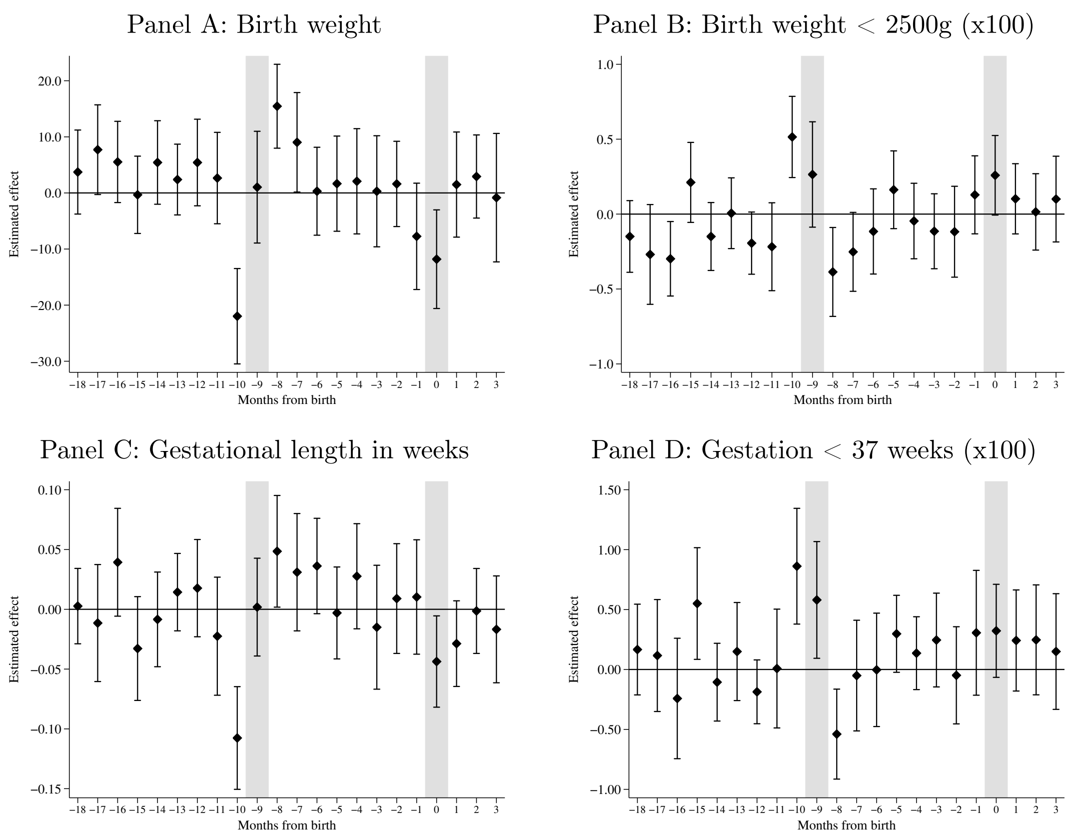
Note: See notes to Figure 3. The birth rates by race are only available starting in 1942.
*Y-axis scale is larger in panel A.2. than in other panels.

Figure 8: Maternal characteristics
Effect of one additional day at 95 °F
1968-2010



Note: See notes to Figure 3. 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.

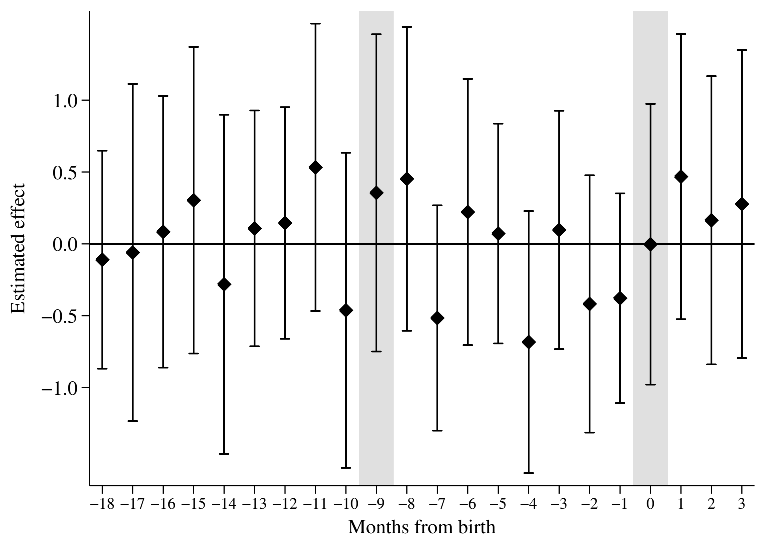
Figure 9: Birth outcomes
Effect of one additional day at 95 °F
1968-2010



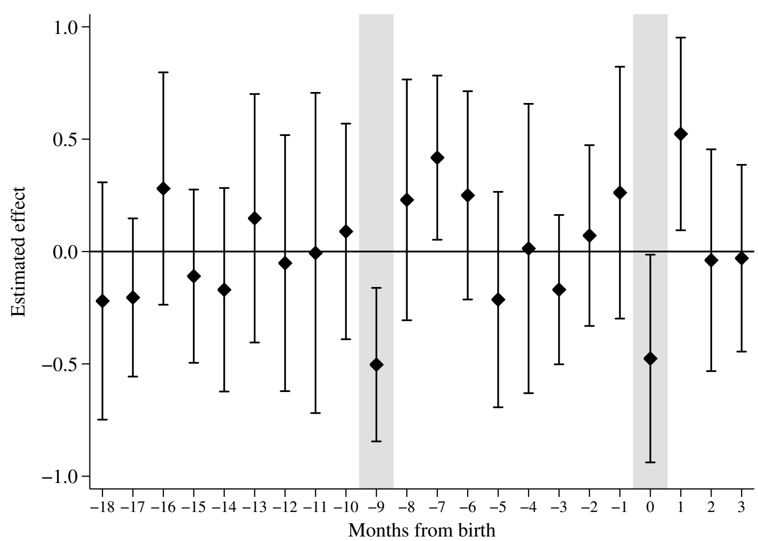
Note: See notes to Figure 3.

Figure 10: Sex ratio analysis
Outcome is the fraction female x 100
1942-1959, 1968-2010

Panel A: 1942-1959, 1968-1970

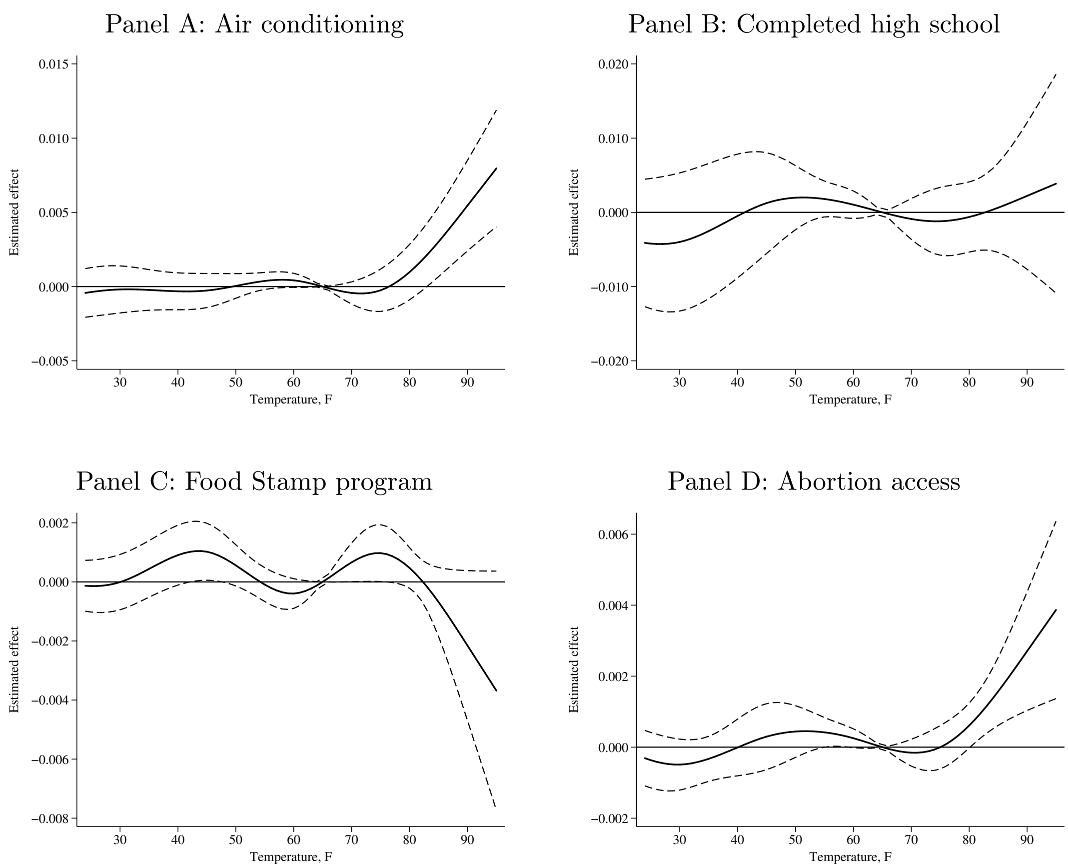


Panel B: 1971-2010



Note: See notes to Figure 3. Data on gender, by state and month, are not available prior to 1942 or between 1960 and 1967.

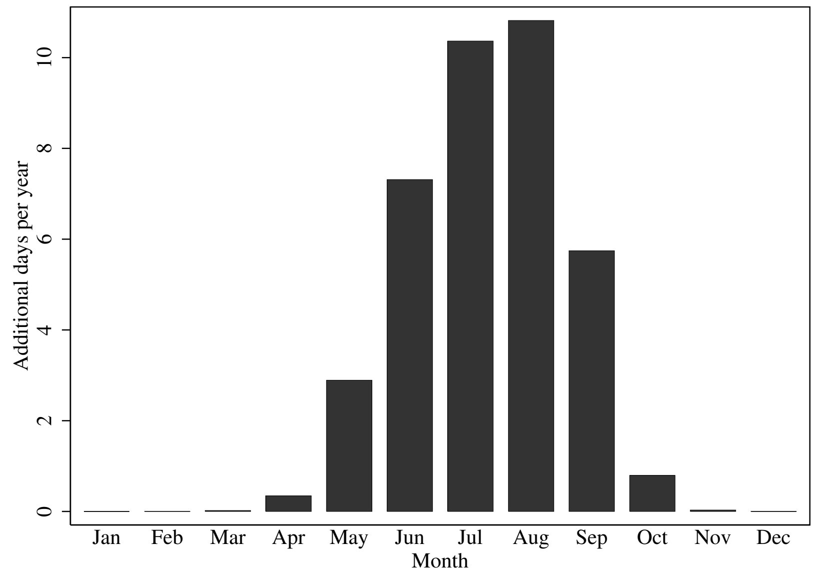
Figure 11: Temperature x modifier interaction
Temperature 9 months prior to birth only
1950-2010



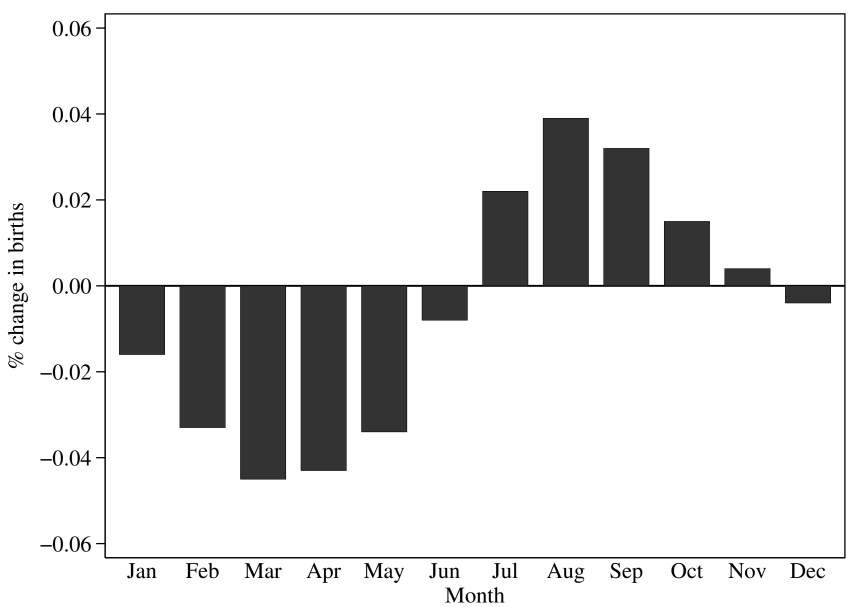
Note: Y-axes scales vary across panels. These are the estimates from equation (1) with a spline in temperature as a main effect, the modifier as a main effect, and the temperature variables interacted with the modifier in question. We present the modifier interaction estimates here only. The model has year-month fixed effects, state-by-calendar-month fixed effects, and state-by-calendar-month quadratic time trends. We control for temperatures in months t-8 through t-13 as well, though only report month t-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 12: Predicted changes by 2070-2099
by calendar month

Panel A: Change in days above 90 °F



Panel B: Change in birth rates



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 from Panel B of Figure 5.

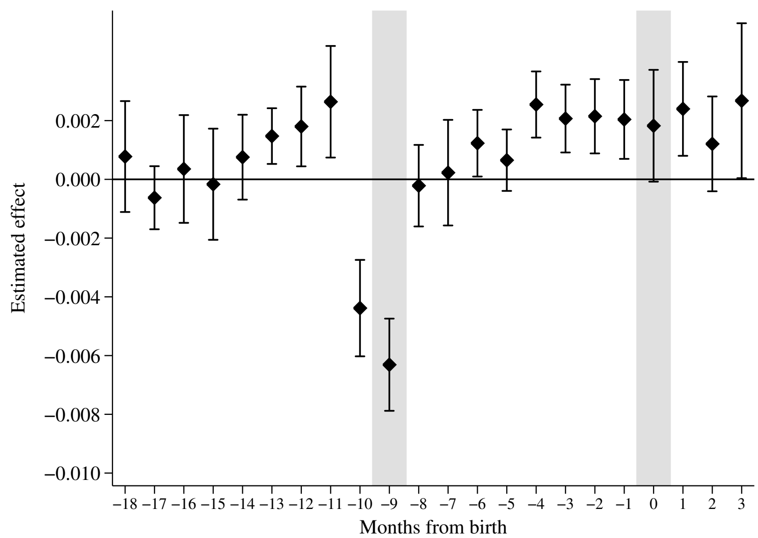
Table 1: Summary of monthly means, by region
1931-2010

Sample:	All states	Northeast	Midwest	South	West
Dailiy births per 100,000 residents	4.73	4.35	4.72	4.91	4.87
Mean temp (F) $<$ 30	.0966	.143	.18	.0301	.0396
Mean temp (F) 30-40	.115	.164	.151	.0752	.0714
Mean temp (F) 40-50	.148	.167	.142	.132	.162
Mean temp (F) 50-60	.175	.162	.145	.16	.265
Mean temp (F) 60-70	.199	.189	.18	.192	.253
Mean temp (F) 70-80	.191	.155	.167	.255	.152
Mean temp (F) 80-90	.0731	.0205	.0341	.153	.0469
Mean temp (F) $>=$ 90	.00275	.000108	.000739	.00215	.0102
Precipitation (1/100 inches) $=$ 0	.71	.648	.693	.714	.806
Precipitation (1/100 inches) 0-50	.221	.272	.245	.201	.157
Precipitation (1/100 inches) 50-100	.042	.0505	.0405	.0472	.0235
Precipitation (1/100 inches) $>$ 100	.0269	.0295	.0209	.0371	.013
Number of states	49	9	12	17	11

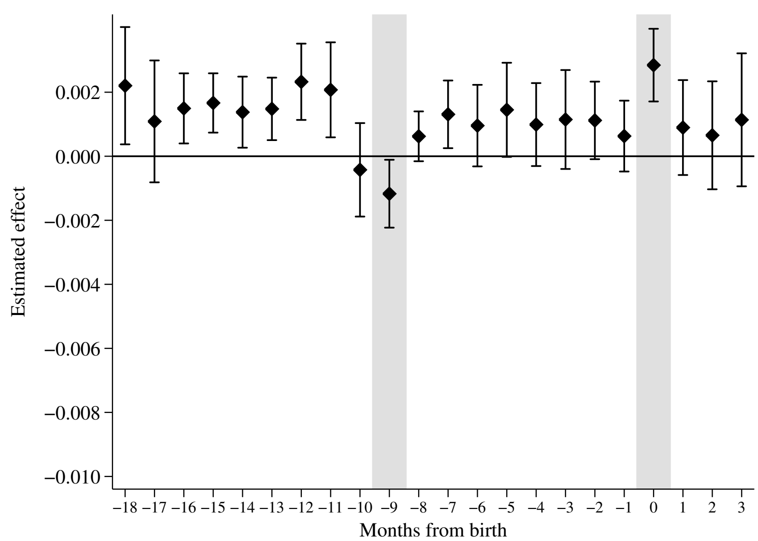
Notes: Averages are weighted by state-year populations.

Figure A1: Using binned temperatures
Effects of increasing temperature from 60-70 to >90 °F
1931-2010

Panel A: 1931-1970



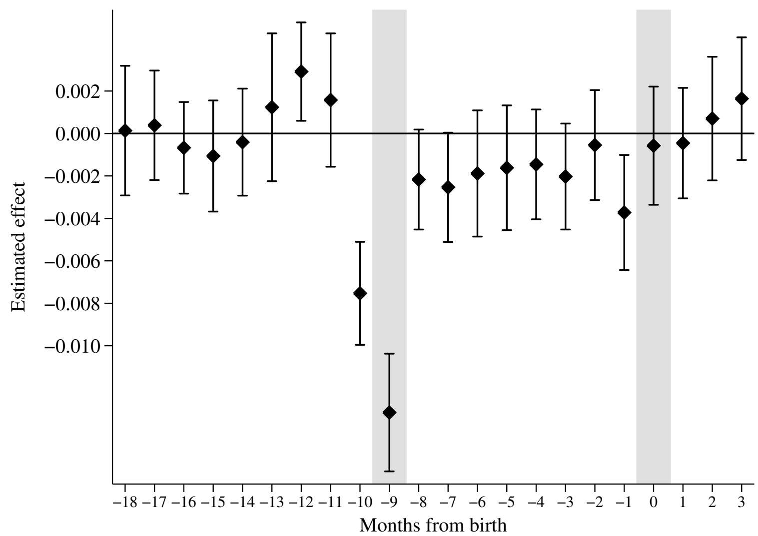
Panel B: 1971-2010



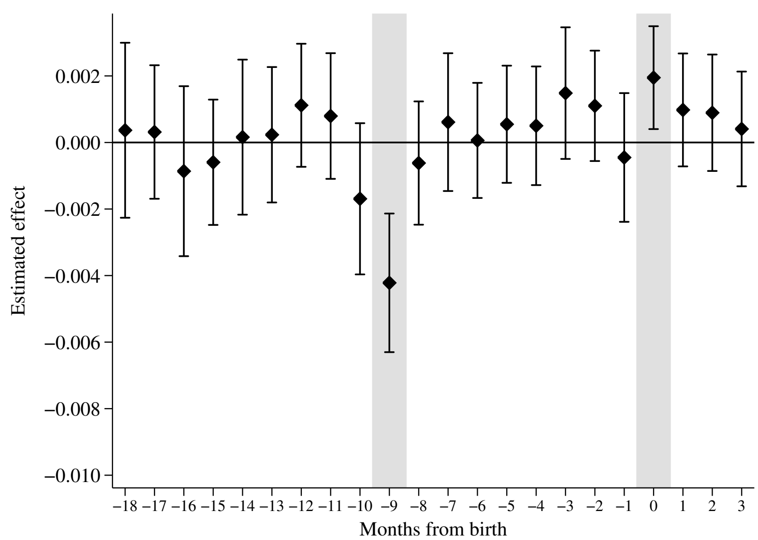
Note: See notes to Figure 3. The estimates come from a model, similar to equation (1), except with an 10 °F binned approach in daily mean temperature (<30, 30-40, 40-50, 50-60, 70-80, 80-90, >90 °F) with days between 60-70 °F as the omitted category. The panel (B) estimates explore the effects of the proportion of the day in a given 10 F bin, where diurnal temperatures are linearly interpolated from the daily maximum and daily minimum temperature.

Figure A2: Using diurnal temperatures
Effects of 24 hours at 90-100 °F relative to 60-70 °F
1931-2010

Panel A: 1931-1970



Panel B: 1970-2010

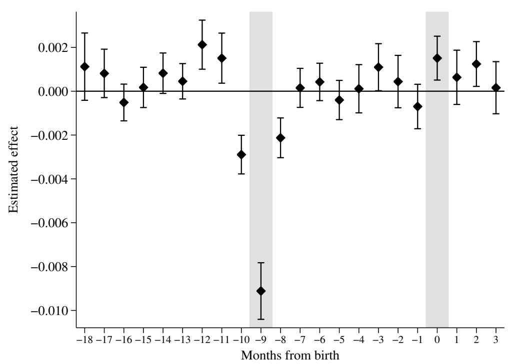


Note: See notes to Figure 3. The estimates explore the effects of the proportion of the day in a given 10 F bin, where diurnal temperatures are linearly interpolated from the daily maximum and daily minimum temperature.

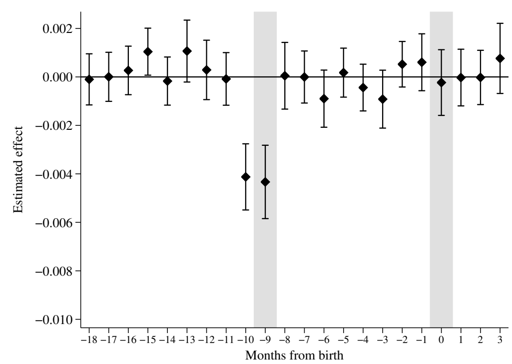
Figure A3: Controlling for humidity
by months-from-birth
1945-2010

Panel A: 1945-1970

Panel A.1: Effect of one additional 95 °F day

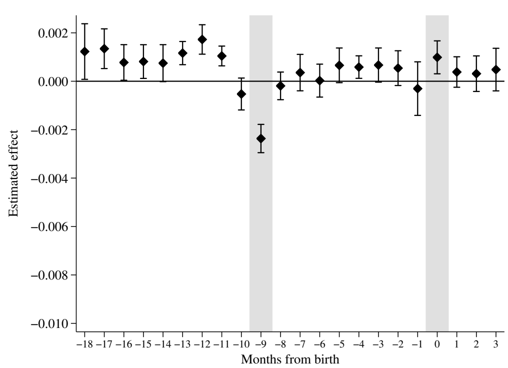


Panel A.2: Effect of one additional 19 g/kg day

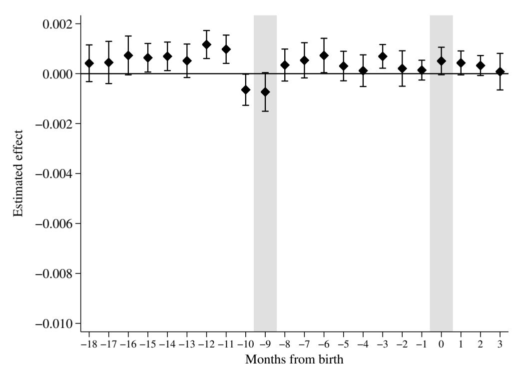


Panel B: 1971-2010

Panel B.1: Effect of one additional 95 °F day

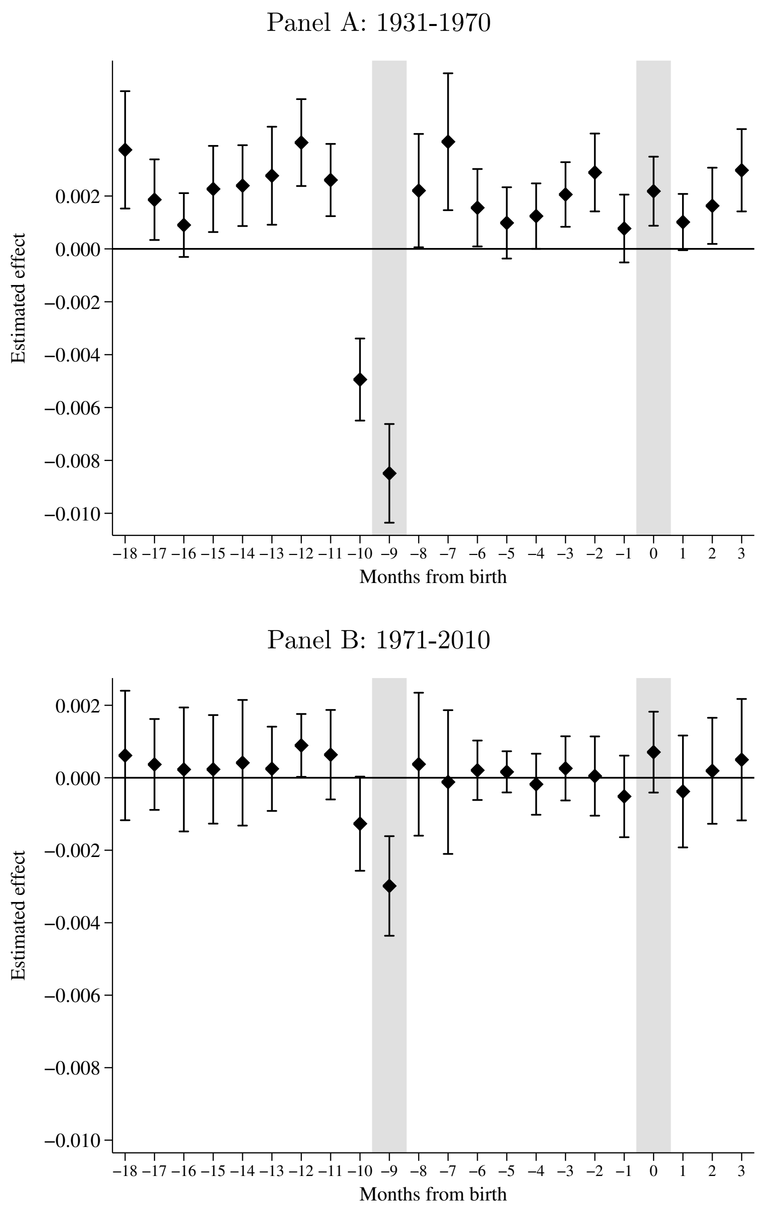


Panel B.2: Effect of one additional 19 g/kg day



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.

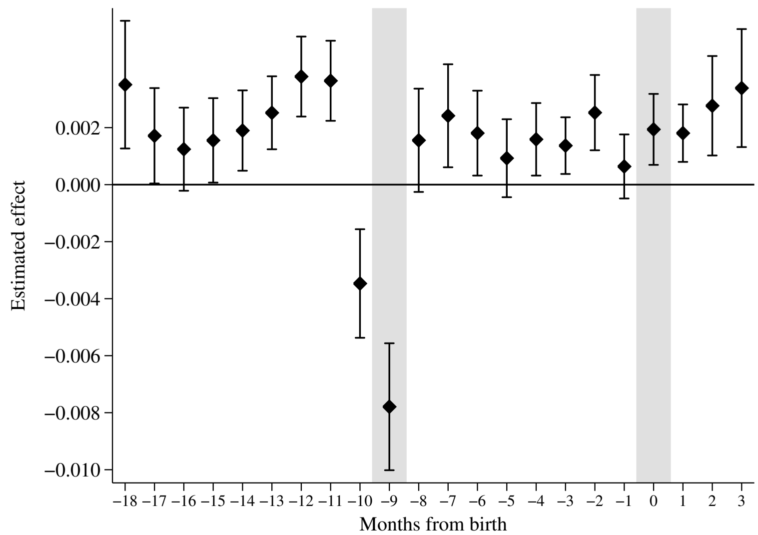
Figure A4: No state-by-month fixed efffects of state-by-month trends
1931-2010



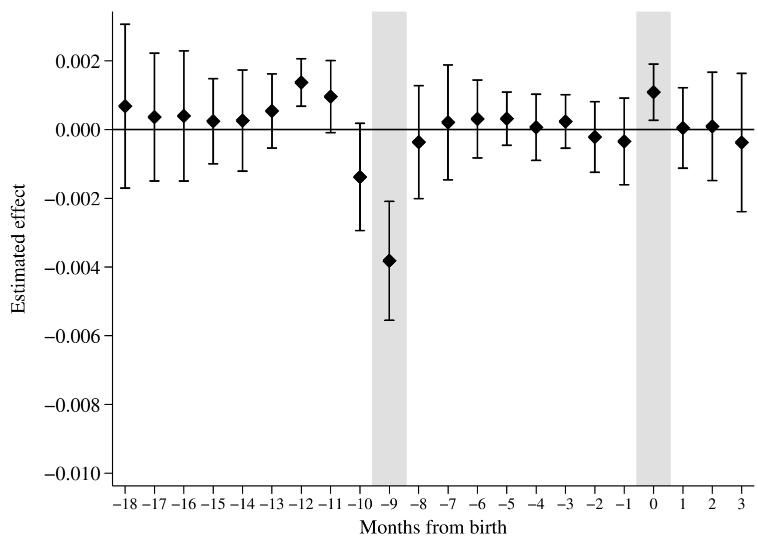
Note: See notes to Figure 3.

Figure A5: No state-by-month trends
1931-2010

Panel A: 1931-1970



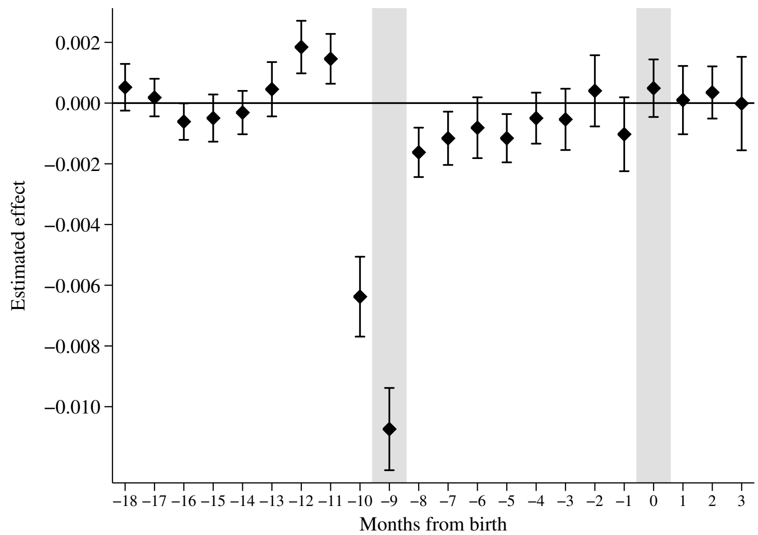
Panel B: 1971-2010



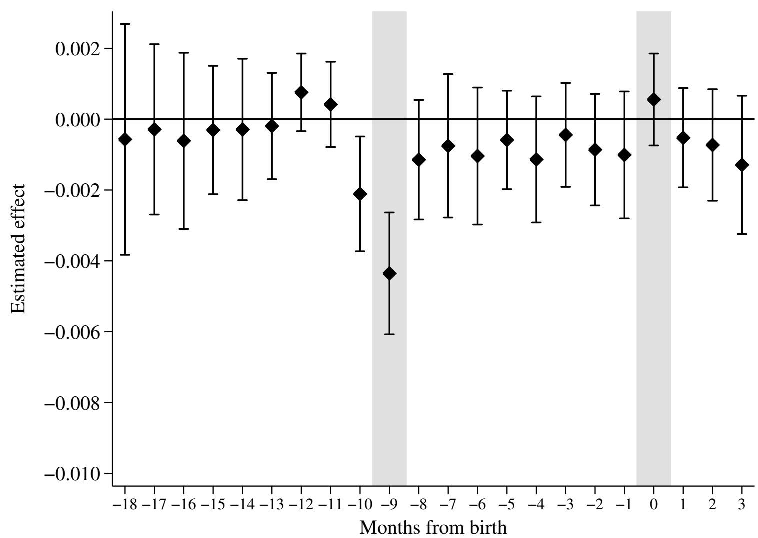
Note: See notes to Figure 3.

Figure A6: Linear state-by-month trends in place of quadratic
1931-2010

Panel A: 1931-1970



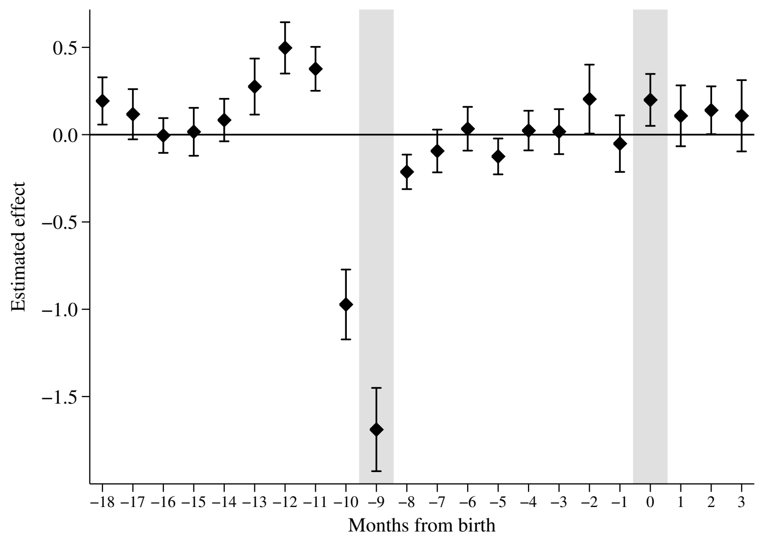
Panel B: 1971-2010



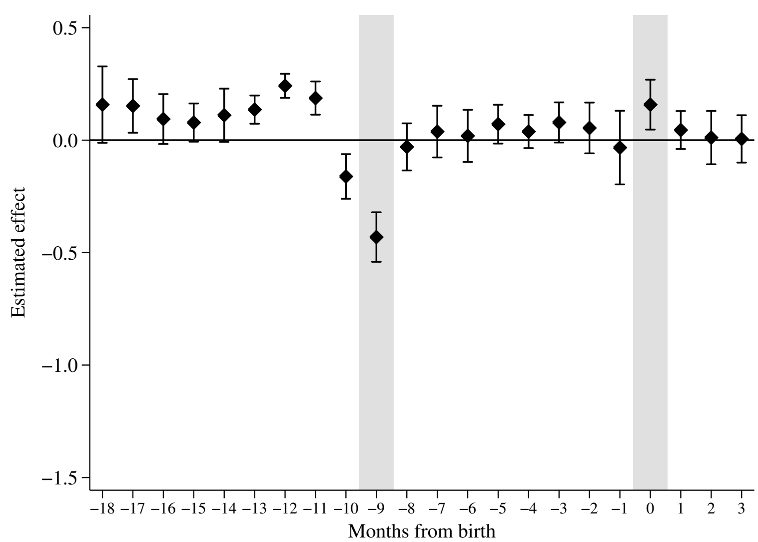
Note: See notes to Figure 3.

Figure A7: Outcome is in levels
Effects of increasing temperature from 65 to 95 °F
1931-2010

Panel A: 1931-1970



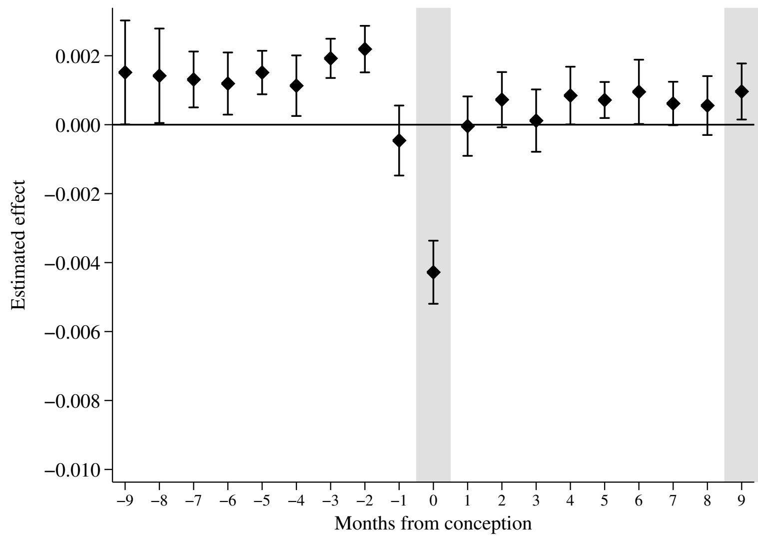
Panel B: 1971-2010



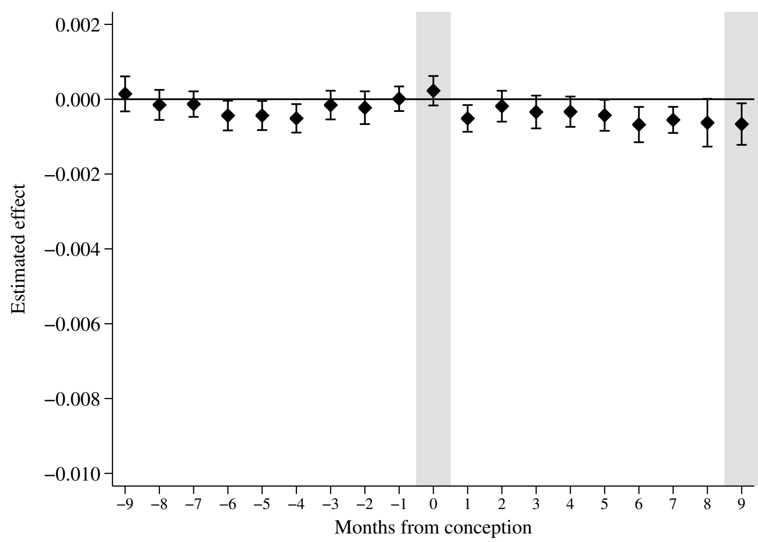
Note: See notes to Figure 3.

Figure A8: Using gestational length to infer conception month
1968-2010

Panel A: The effects of each additional day at 95 °F

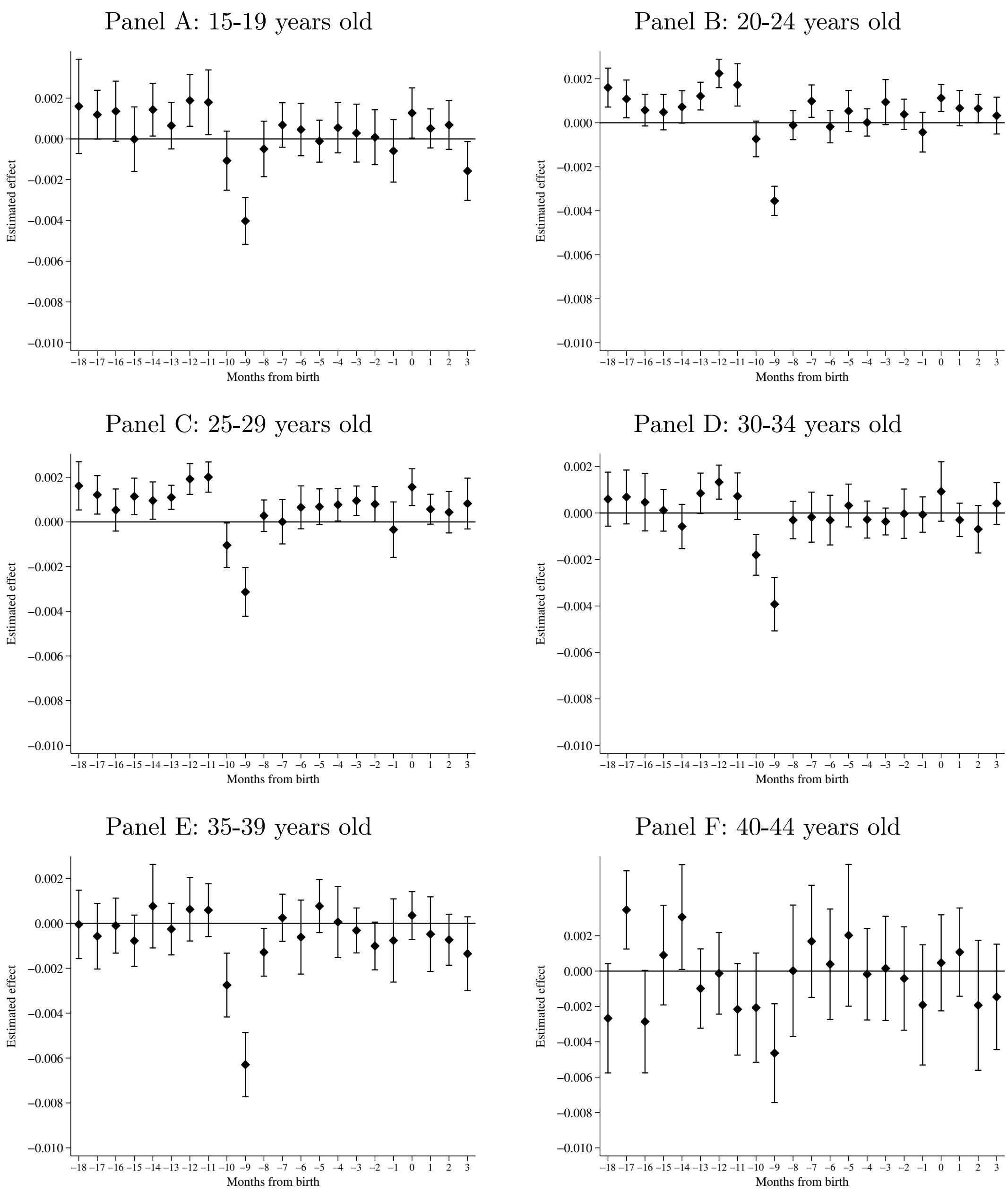


Panel B: The effects of each additional day at 35 °F



Note: See notes to Figure 3. Month of conception by subtracting gestational length from the date of birth. Note that the day, within the calendar month, of birth is unavailable after 1988. We assume the day of birth occurs on the 15th of the month in these cases. In the 12% of cases where gestational length is missing, we assume a 40 week gestational length.

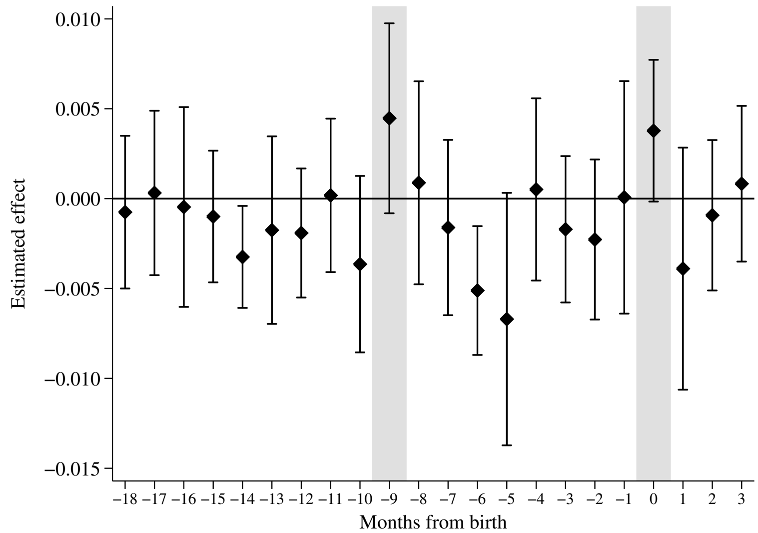
Figure A9: Marginal effect of an increase in one day's temperature from 65 °F to 95 °F
By age group
1968-2010



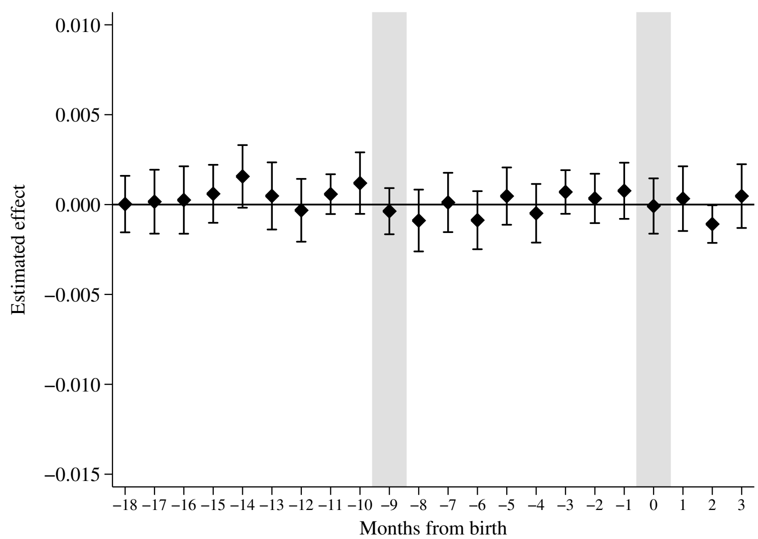
Note: See notes to Figure 3.

Figure A10: Neonatal mortality estimates
Outcome: Log of the average daily neonatal mortality rate
1959-2004

Panel A: Effect of temperature increase from 65 to 95 °F

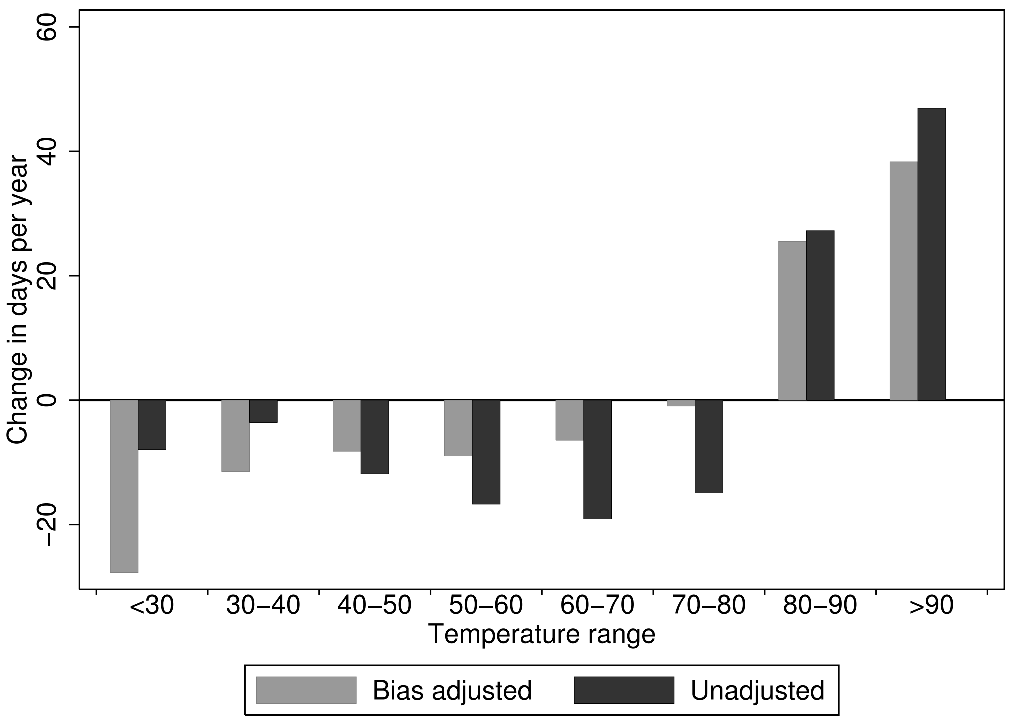


Panel B: Effect of temperature decrease from 65 to 35 °F



Note: See notes to Figure 3. 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 data are not publicly available, at the state-month level, prior to 1959 or after 2004.

Figure A11: Climate change temperature projections, Hadley CM3 A1F1 model



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.

Table A1: Climate change projections
Change in the log of the daily birth rate

	Census region								
Entire US	New England	Mid Atlantic	E. N. Central	W. N. Central	South Atlantic	E. S. Central	W. S. Central	Mountain	Pacific
-0.006	-0.013	-0.011	-0.009	-0.005	-0.007	-0.004	0.000	-0.005	-0.006
(.008)	(.006)	(.007)	(.008)	(.01)	(.008)	(.011)	(.013)	(.006)	(.005)

Notes: Panel A predictions combine the estimates from Panel B of Figure 5 estimates for the 1971-2010 period with the bias-adjusted Hadley CM3 A1F1 model. Standard errors are in parentheses.