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Authors:

Michael Geruso (UT-Austin & NBER)

Melissa LoPalo (Montana State University)

Dean Spears (UT-Austin & IZA)

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PAA 2021 Extended Abstract

Michael Geruso* Melissa LoPalo† Dean Spears‡

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Abstract

A critical open question at the intersection of climate change and demography is the relationship between extreme climatic conditions and human fertility. In this paper, we study how temperature and humidity exposure affects human fertility in the developing world. We combine 142 rounds of Demographic and Health Survey datasets from low and middle income countries around the globe to create the most complete catalogue of fertility patterns linked to weather data to date. Importantly, our analysis separates the direct impacts of weather from other place-specific seasonal factors that may influence fertility. We find that exposure to extreme heat—relative to a village or urban area’s *typical seasonal temperature profile*—lowers birth rates nine months later. We find that the rebound in fertility in subsequent months is incomplete, suggesting the fertility declines due to extreme weather are not completely reversed with later additional childbearing. These results have significant implications for climate change, both in describing the potential fertility consequences of climate change and because optimal climate policy depends crucially on the expected size of future generations.

*University of Texas at Austin and NBER

†Montana State University. Email: melissa.lopalo@montana.edu

‡University of Texas at Austin and Economics and Planning Unit, Indian Statistical Unit, Delhi and r.i.c.e.

What consequences will climate change have for fertility in developing countries? The fact that birth rates vary with the seasons is a long-established fact, and a sizable literature suggests that temperature is one of the root causes. Prior papers link abnormally hot summers with unusually low birth rates 9-10 months later, suggesting that conceptions decline in the heat (e.g. [Seiver \(1989\)](#); [Lam and Miron \(1996\)](#)). More recently, [Barreca, Deschenes and Guldi \(2018\)](#) investigate the scope for adaptation through delayed conception. They find that one additional day with a mean temperature above 80 degrees Fahrenheit causes a decline in birth rates 8 through 10 months later, but that birth rates partially rebound in months 11-13.

Much of the prior evidence is derived from high income countries like the United States. However, little is known about the causal impacts of extreme temperature on fertility in developing countries. There are many reasons to believe that responses may be significantly different in developing countries, where average temperatures and humidity levels are higher, fertility preferences and behaviors differ, and where many people have less ability to avoid exposure to extreme temperatures (such as via indoor, climate controlled living and working spaces).¹ The potential for different impacts across the rich and poor world is particularly important in light of climate change: people in developing countries will be exposed disproportionately to increasingly frequent extreme temperature events, and quantifying impacts on fertility will have implications for optimal climate policy ([Greenstone and Jack, 2015](#)).

The literature has overlooked developing countries principally because of data availability: developing countries are highly climate-vulnerable, but lack vital registration systems to record all births ([Setel et al., 2007](#)). We overcome this challenge by appending 142 nationally-representative survey-reported birth histories from 58 developing countries. The result is a full sample of over 100 million woman-months that we combine with high-resolution global weather data using emerging supercomputing techniques for the econometrics big data. This is a methodological advance over prior literature that studies demographic aggregates (such as fertility rates) and therefore cannot exploit woman-level heterogeneity.

We estimate the impacts of weather on survey-reported fertility, following the identification strategy of relying on place-specific “surprise” weather using high-density fixed effects (see, e.g., [Barreca,](#)

¹Furthermore, previous literature indicates linkages between weather and infant mortality (e.g. [Grace et al. \(2015\)](#)) and infant mortality and fertility (e.g. [Nobles, Frankenberg and Thomas \(2015\)](#)), providing an additional mechanism through which temperature may affect fertility that is less likely to be at play in developed countries.

Deschenes and Guldi (2018), Geruso and Spears (2018), and LoPalo (2019)). This nets out any other seasonal factors that differ across locales and that may affect fertility. For example, if August is typically hot in the region of interest, or if June is typically a harvest month, our strategy will net out any correlations between fertility patterns and such predictable seasonal variation, identifying impacts only on the basis of deviations from typical weather.

We also examine dynamic changes in birth rates in response to exposure to extreme temperature. This allows us to ask whether decreases in fertility nine months following an unusually hot month are compensated with increases in fertility in the following months. Finally, and in contrast with prior work, we examine the impacts of both temperature and humidity, as recent research (Geruso and Spears, 2018) suggests that humidity is an important mediator of the physiological impacts of temperature that affect demographic outcomes.

1 Data and Methods

Our dataset combines respondent birth histories from Demographic and Health Survey (DHS) datasets with gridded global weather data from the Princeton Meteorological Forcing Dataset (henceforth the Princeton Data).

Dependent variables: Survey-reported birth history. DHS surveys are nationally and regionally representative, cross-sectional surveys that have been conducted in dozens of countries. The survey elicits a complete reproductive history, including births and instances of infant mortality, from each adult female in selected households. We use this birth history to create a respondent-month level panel of birth events looking back seven years from the date of interview. We use data from all DHS survey waves that contain GIS information on selected survey clusters, amounting to 142 survey rounds from 58 countries. For this extended abstract, we select a 30 percent random sample of survey clusters to include in our dataset; the 30 percent sample amounts to 44.3 million respondent-months.

Independent variables: GIS weather history. The Princeton Data is a global gridded reanalysis dataset, indicating that it combines observational weather data from sources such as weather stations with a weather model, allowing it to improve precision in areas with few weather measurements. The data are available at the 0.25 latitude/longitude degree level eight times daily; we use this information to calculate daily averages. Our main weather variable of interest is wet bulb temperature, which is a nonlinear function of temperature and humidity, designed to incorporate the

physiological impacts of humid heat (Sherwood and Huber, 2010). Because the DHS birth data is at the monthly level, we create a monthly count of days with average wet bulb temperatures that fall into eight bins: <30 degrees Fahrenheit, 30-40 degrees, 40-50 degrees, 60-70 degrees, 70-80 degrees, 80-85 degrees, and >85 degrees. The excluded category is 50-60 degrees, so that our regression results are interpretable as the impact on birth rates of replacing a day with an average wet bulb temperature of 50-60 degrees Fahrenheit with a day in the bin of interest.²

Empirical strategy: Fixed effects for local seasonality. Our baseline regression examines the impacts of exposure to an additional day in each weather bin on probability of giving birth, relative to exposure to a 50-60 degree day. Similarly to Barreca, Deschenes and Guldi (2018), we examine the impacts of exposure that occurred up to 24 months prior and three months after the month of interest. The regression takes the form:

$$B_{ict} = \sum_{k=-3}^{24} \sum_j \beta_{j,t-k} \cdot Exposure_{jc,t-k}(T_j) + X_{it} + \alpha_{my} + \eta_{cm} + \epsilon_{ict} \quad (1)$$

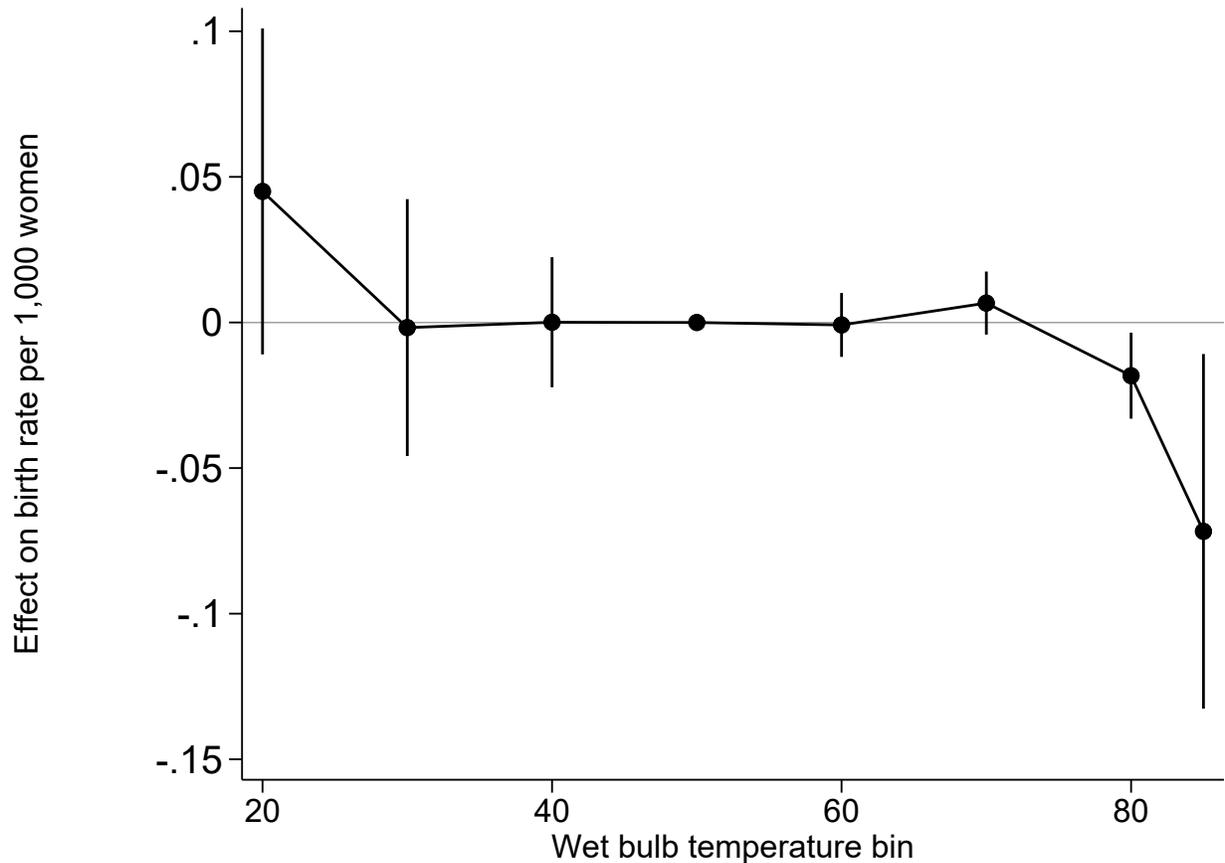
where B_{ict} is a dummy variable for whether respondent i in survey cluster c gave birth in month-year t . We scale the outcome variable by 1,000, so that the regression results are interpretable as effects on fertility rates per 1,000 women. $Exposure_{jct}$ indicates the number of days in month t that the respondent was exposed to a daily average wet bulb temperature in bin j . The coefficients of interest are $\beta_{j,t-k}$, which can be interpreted as the change in birth rates resulting from exposure to a day in wet bulb bin j in month $t - k$ instead of a 50-60 degree day. X_{it} is a vector of household level controls, in this case controls for household electrification and the DHS wealth index. α_{my} are year-by-calendar-month fixed effects, which control for any time-varying factors that may correlate with both weather and birth rates, and η_{cm} are survey cluster-by-calendar month fixed effects, controlling for place-specific seasonality in both temperatures and birth rates. The inclusion of these fixed effects means that we are identifying our effects from variation in weather that differs from the usual seasonal variation in temperatures for a certain cluster. That is, we are examining responses in birth rates to “surprising” weather variation. Standard errors are clustered at the level of the survey cluster.

² Following Geruso and Spears (2018), we merge the DHS data with the Princeton data by locating the four gridpoints in the Princeton data that surround each DHS survey cluster. We then take an average of each weather variable for the four surrounding gridpoints, weighted by the inverse distance between each gridpoint and the cluster.

2 Preliminary results

Figure 1 shows the results of Equation 1, but only displays the results for exposure to weather 9 months prior. Our preliminary results suggest that extremely hot wet bulb temperature days significantly depress birth rates 9 months later, indicating a decline in conceptions in months with an unusual number of hot and humid days.

Figure 1: Exposure to Extreme Wet Bulb Temperatures Reduces Births 9 Months Later

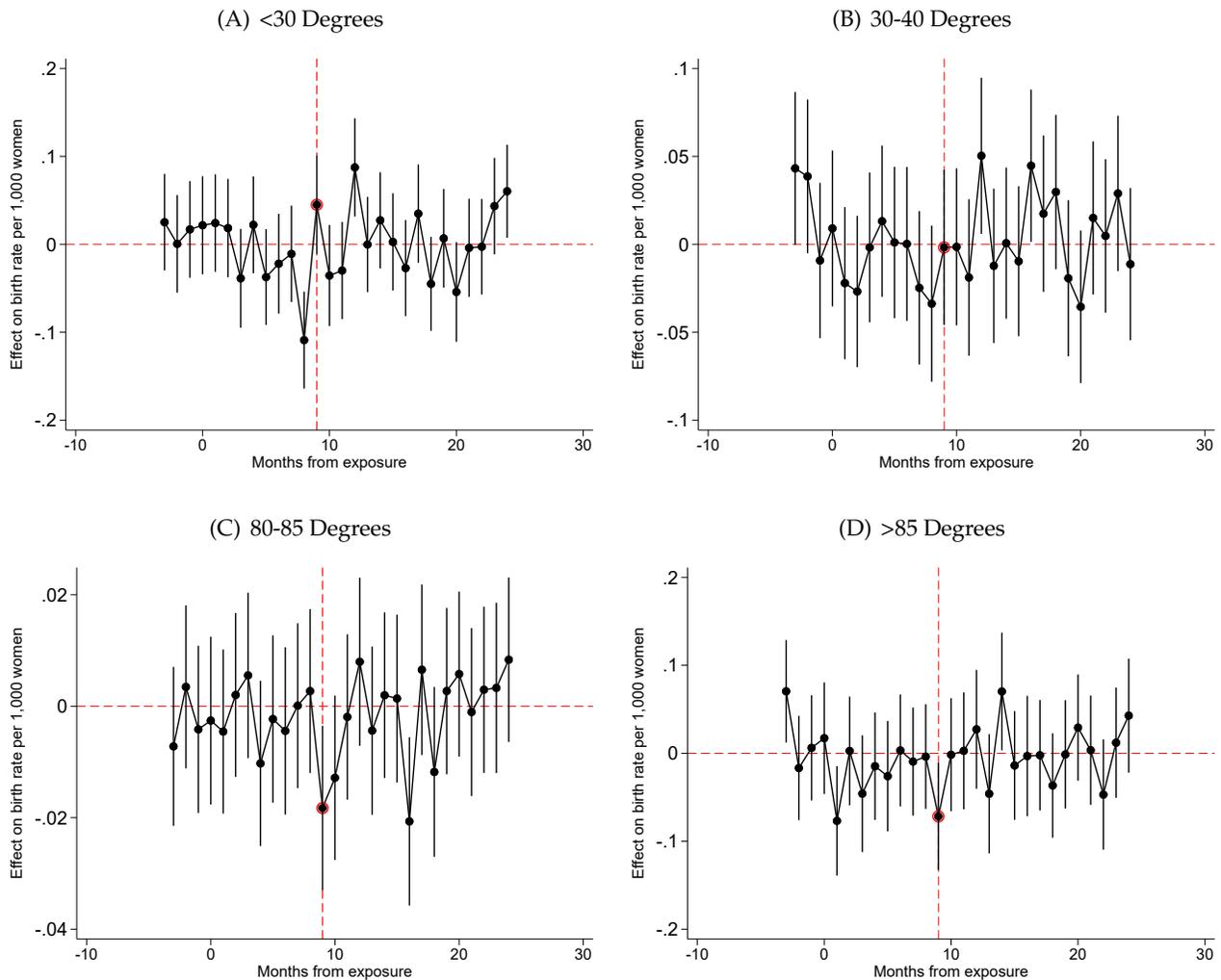


Note: This figure shows the results of a respondent-month level regression using birth rates per 1,000 respondent as the outcome variable. The independent variables of interest are the number of days that the respondent was exposed to in each wet bulb temperature bin 9 months prior. The regression also includes wet bulb temperature bins for up to 24 months prior and 3 months after the month of interest, but only the coefficients for 9 months ago are displayed. The regression controls for household characteristics, calendar month-year fixed effects and survey cluster by calendar month fixed effects. Standard errors are clustered at the level of the survey cluster. Point estimates and 95% confidence intervals are shown.

Figure 2 explores the dynamic impacts of extreme temperature exposure on fertility. Each subfigure examines the impacts of an additional day of exposure to wet bulb temperatures in a different bin over time: impacts of exposure up to 24 months before and three months after the month of interest

are displayed for each bin. Panels A and B display coefficients on the <30 degree and 30-40 degree bins, respectively. These graphs suggest that cold temperatures depress birth rates 8 months after exposure, but also that there is significant bounceback in birth rates one year later, suggesting that conceptions are in large part simply pushed back in time. On the other hand, panels C and D suggest that exposure to hot and humid days depresses fertility 9 months later with incomplete subsequent rebound. We can add together the coefficients on months 0 to 24 to get an estimate of the total impact on fertility up to 2 years later: the results indicate that exposure to an additional day with a wet bulb temperature above 85 degrees, for example, produces a decline in birth rates of -0.19 per 1,000 women.

Figure 2: Fertility Rebounds a Year after Exposure to Cold Temperatures; Incomplete Rebound after Exposure to Hot and Humid Temperatures



Note: This figure shows the results of a respondent-month level regression using birth rates per 1,000 respondent as the outcome variable. The independent variables of interest are the number of days that the respondent was exposed to in each wet bulb temperature bin for up to 24 months prior and three months after. Panels A-D display coefficients by months from exposure for the <30 degree, 30-40 degree, 80-85 degree, and >85 degree wet bulb bins, respectively. The regression controls for household characteristics, calendar month-year fixed effects and survey cluster by calendar month fixed effects. Standard errors are clustered at the level of the survey cluster. Point estimates and 95% confidence intervals are shown.

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