CAHIER DE RECHERCHE #2102E
DÉPARTEMENT DE SCIENCE ÉCONOMIQUE
FACULTÉ DES SCIENCES SOCIALES
UNIVERSITÉ D'OTTAWA

WORKING PAPER #2102E
DEPARTMENT OF ECONOMICS
FACULTY OF SOCIAL SCIENCES
UNIVERSITY OF OTTAWA

Timing Matters: Prenatal Climate Shocks, Sex Ratio, and Human Capital [1]

Landry Kuate[2], Roland Pongou[3] and Nicholas Rivers[4]

April 15, 2021

[1] We thank Louis-Philippe Beland, Jason Gared, Paul Makdissi, and Louis-Philippe Morin for helpful comments. We gratefully acknowledge comments from participants at the 29th Annual Conference of the Canadian Resource and Environmental Economics Association (CREEA) and the 59th annual congress of Societé canadienne de science économique (SCSE). Landry acknowledges the Soft-Funded Research Grant from Institute of the Environment of University of Ottawa.
[2] Department of Economics, University of Ottawa, lkuat097@uottawa.ca
[3] Department of Economics, University of Ottawa, rpongou@uottawa.ca
[4] Graduate School of Public and International Affairs // Institute of the Environment, University of Ottawa, nrivers@uottawa.ca

Abstract

This paper offers new causal evidence on how the timing of prenatal temperature shocks affects fetal health, sex ratio at birth, and early-age human capital. Analyzing data on nearly 2 million live births from sub-Saharan African countries and exploiting exogenous spatial and temporal variation in monthly temperature, we uncover three findings. First, we find that a cold temperature shock decreases the likelihood of a male birth. This effect is non-linear, being larger in the first and third trimesters of pregnancy. It is also highly heterogeneous, being larger for older women, higher parity births, and rural areas. Second, combining our empirical estimates with a climate model, we find that the number of fetal deaths caused by climate change will rise from 200 to 400 per 100,000 live births by 2050 throughout sub-Saharan Africa. Third, in contrast to their differential effect on fetal mortality, prenatal temperature shocks increase infant mortality more for females than for males, suggesting that only healthier male fetuses survive to adverse in utero conditions. Our analysis implies that the design of policies to avert the negative impacts of climate change on children should account for stages of fetal development.

Keywords: Climate Change; Timing of Prenatal Temperature Shocks; Impact Heterogeneity; Fetal Mortality; Sex Ratio; Infant Mortality; Human Capital; Sub-Saharan Africa.

JEL classification: Q54, I12, I15, J13, O15.

1 Introduction

The ratio of men to women has been shown to affect important social and economic outcomes including marriage (Angrist, 2002; Abramitzky et al., 2011), entrepreneurship (Wei and Zhang, 2011), crime rates (Edlund et al., 2013; Cameron et al., 2019), female labor force participation (Amuedo-Dorantes and Grossbard, 2007), exchange rates (Du and Wei, 2011), and sexual infidelity and diseases (Kang and Pongou, 2019), among others. Imbalanced sex ratio is explained by male-female disparities in mortality. Studies investigating the causes of these disparities find that they vary significantly across life stages. However, it is also generally acknowledged that knowledge of these causes is still incomplete, especially in very early life stages when critical development takes place. In particular, the economic literature has paid little attention to the period of fetal formation and development, despite mounting empirical evidence showing that circumstances experienced in utero have significant impacts on later-life outcomes (Barker, 1997; Almond et al., 2018). The general lack of knowledge about the causes of sex imbalance in very early life constitutes an important constraint on policy actions likely to avert its negative socioeconomic impacts.

This paper offers new causal evidence on how the *timing* of prenatal temperature shocks affects fetal health, sex ratio at birth, and sex-specific early-age human capital. We achieve a threefold goal. First, we examine the impacts of temperature shocks during pregnancy on sex differences in fetal mortality in sub-Saharan African countries. The absence of vital statistics on fetal deaths in most societies means that the true estimate of this relationship is hard to measure. We advance by leveraging the insight that males and females are differently susceptible to shocks in utero (Orzack et al., 2015). This differential susceptibility determines male-female differences in fetal death and hence sex ratio at birth, an important outcome. Second, using the insight from the first analysis, we estimate a lower bound on the impact of temperature shocks on total fetal deaths, and apply a climate model to predict the long-term fetal mortality due to predicted ambient temperature changes throughout sub-Saharan Africa. Third, we extend our analysis by estimating the effect of prenatal temperature shocks on infant mortality. To the extent that in utero mortality selection due to temperature differs for male and female fetuses, the effect of prenatal temperature on infant mortality may differ across the sexes, and it is likely that the direction of this difference will be opposite to its differential effect on fetal mortality. Our study therefore sheds new light on how the effects of prenatal temperature differ for prenatal and postnatal outcomes. More importantly, by documenting how the timing of prenatal temperature shocks matters, our analysis offers novel findings with direct implications for how the design of policies aimed at averting the negative impacts of climate change on early-life human capital formation should account for stages of fetal development.

Our analysis is related to recent research showing that human demographic impacts are likely to be amongst the most severe costs of climate change, with impacts on both mortality (Carleton et al., 2018; Barreca et al., 2016) and fertility (Barreca et al., 2018; Dessy et al., 2019). Such mortality-related effects could be even more harmful for fetuses and infants who are especially sensitive to hot temperature due to the early development stage in thermoregulatory and nervous system (Young, 2002; Knobel and Holditch-Davis, 2007). However, while there is a growing literature seeking to understand the impacts of prenatal shocks on subsequent human capital formation throughout the individual lifetime (Isen et al., 2017; Wilde et al., 2017), little research has studied how environmental insults directly affect humans in utero or the viability of the embryo or fetus — whether or not it produces a live birth. Moreover, little attention has been paid to how the timing of prenatal shocks matters. Prior studies have discussed the biological fragility of the male fetus which is at great risk of death or damage from almost all the obstetric catastrophes and external maternal stress including climate shocks (Catalano et al., 2008; Kraemer, 2000). Therefore, prenatal shocks could impair offspring sex ratio at birth as a result of fetal death as well as sex differences in postnatal outcomes, thus impacting the long-term population gender composition of society, a key driver of social movements such as marriage markets, labour force participation, or crime rates. Examining the effects of climatic conditions experienced during in utero period is therefore crucial for long-term social and economic stability.

In investigating the question of how ambient temperature at different stages of fetal development (or at different periods during pregnancy) affects fetal outcomes, sex ratio at birth, and sex-specific infant mortality, we focus our attention on how environmental conditions affect the likelihood of fetal maturation only after conception.[1] Exposure to weather shocks among pregnant mothers can affect fetal death and offspring's sex ratio through three potential mechanisms that impact the fetus either directly or indirectly through mother's responses. These include: *(i)* biological effect induced by heat stress which might result in several health issues including risk of placenta abruption (He et al., 2018), preterm and stillbirth (Carolan-Olah and

[1] We do not study the effect of temperature on sex determination at conception. Temperature may influence primary sex determination by the variable fertilization success of X- and Y- bearing sperm (McLachlan and Storey, 2003). Moreover, there is evidence supporting that ambient temperature and stressful environmental conditions affect the steroid concentrations of ovarian follicles (Wolfenson et al., 2000; De Rensis and Scaramuzzi, 2003), and may also impair sperm mobility and potentially promoting female biased birth sex ratio (Fukuda et al., 1996). In some specifications of our model, we account for these two channels by analyzing the effect of temperature after conception has already occurred.

Frankowska, 2014; Strand et al., 2011b) and pregnancy loss (Beltran et al., 2014); *(ii)* behavioral mechanism involving a change in consumption habits (food selection, appetite loss); and *(iii)* income, owing to negative impacts of extreme temperature on agricultural yields and thus household resources.

Sub-Saharan Africa is an ideal setting for our analysis. It is a rapidly developing region with wide ecological, climatic and cultural diversity. By 2050, its population is projected to approach 2 billion people (DESA (2015)), a dynamic which comes with both opportunities and challenges to policy makers. At the same time, the region is undergoing permanent changes in climatic conditions. However, little is known about how these changes will affect different population groups. There is little investment aimed at protecting against climate shocks, and individuals in the region are in majority involved in out-door activities (agriculture, outside trading activities, etc.) and therefore are exposed to weather variations including extreme temperature. In addition, economic activities are dominated by agriculture, which is highly dependent on climatic conditions. As a consequence, a weather shock that leads to a change in agricultural yields may reduce household resources (Brown and Funk, 2008; Hertel, 2016) and affect fertility and reproductive health (Dessy et al., 2019; Grace, 2017). However, the distributional effect of climate shocks across different population subgroups in this region has been little studied. Our examination of the effects of temperature shocks at different stages of pregnancy on sex difference in fetal death and infant mortality contributes to filling this gap.

We use data from 85 Demographic and Health Surveys (DHS) with geo-coded information collected in 34 Sub-Saharan African countries between 1980 and 2010. The DHS collects information on complete fertility history from mothers aged 15-49 years old and their children. We link these surveys to historical gridded monthly air temperature and precipitation data from the University of Delaware's air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). We identify weather conditions experienced during the prenatal period for all children born to women surveyed in the DHS. To estimate the impact of in-utero mean-temperature on the sex ratio at birth and sex-specific infant mortality, we use a non-linear specification with region and month of birth fixed effects.

Our results show that temperature shocks have differential impacts on male and female fetuses. We find that cold temperatures decrease the likelihood of live male births. Moreover, the effect of a cold temperature is more pronounced during the first and third trimesters of pregnancy, suggesting that these periods are critical windows of fetal development, especially for male fetuses. The impact of hot temperatures on sex ratio at birth is more ambiguous. Our findings are robust to alternative specifications including alternative functional forms, different controls, and inclusion of different fixed effects. We show that our main findings survive several robustness checks.

We document possible mechanisms driving our findings by examining heterogeneity in the effect of ambient temperature on fetal outcomes. These mechanisms may be biological, behavioral, or/and operating through income. In our analysis, they are captured using mother's age at delivery, child birth order, and place of residence (either urban or rural). Our findings show that the adverse impact of a cold prenatal temperature shock is offset in younger mothers with fewer children. We also find that cold prenatal temperature is more harmful for mothers who live in rural areas compared to their counterparts living in urban areas. These results are consistent with the notion that the adverse effects of poor environmental conditions are partly mediated through mother's health and reduced income for households whose livelihoods depend on weather conditions.

Quantifying the causal impact of temperature during pregnancy on sex ratio at birth raises several econometric challenges. First, while it is generally assumed that the gestational length is a random variable, it also acknowledged that it could be endogenous to environmental insults in-utero (Schifano et al., 2016). The randomness of gestational length implies that the time of conception is difficult to determine.[2] Therefore, this raises a classical measurement errors concern as we imperfectly measure the temperature at the time of conception. We show that this is a minor concern given that our main findings change little when we vary the assumed length of pregnancy period from 9 months to 8 or 10 months. Second, we assume place of birth to be the same as the place of residence, which might not be the case as a mother might have moved after conception or before birth. To deal with this issue, we examine if the effect of temperature shocks varies according to how long a mother has been living in her place of residence, and we do not find that it varies. Lastly, although human sex ratio at birth allows to capture both natural sex selection and culling effects, it is difficult to test these effects separately. However, we provide some evidence that the impacts of temperature shocks on sex ratio at birth occur primarily through culling (or fetal deaths), but we cannot exclude the possibility that a portion of the impact occurs via sex selection.

As our second goal, we use our estimated marginal effects of temperature on sex ratio at birth to quantify a lower bound on climate-related fetal mortality. Our results suggest that at least 200 fetuses per 100,000 live births are lost due to adverse temperature throughout sub-Saharan

[2]Changes would be, generally, on the range of days and thus their effect would be minimal in the context of full-term pregnancies, (Jukic et al., 2013).

Africa. In addition, we use the climate models from the Coupled Model Intercomparison Project 5 (CMIP5) under the Representative Concentration Pathways (RCP) 8.5 scenario, to predict that fetal deaths will increase to around 400 per 100,000 live births by 2050 due to changes in temperature. The estimation of fetal mortality is considered as a lower bound since our setting captures only the unbalanced effect of average temperature on a given sex; that is, if the change in temperature affects identically male and female fetuses, we do not measure it.

As our third and final goal, we generalize the hypothesis that temperature shocks experienced at different stages of pregnancy operate by mostly affecting fetuses with low biological endowment by exploring their effect on sex differences in infant mortality. We find that the effect of a temperature shock occurring during pregnancy sex-specific infant mortality is opposite to its effect on sex ratio at birth. Now, a cold temperature shock decreases the probability of infant mortality, and this effect is more pronounced among males compared to females. Moreover, while hot prenatal temperature increases infant mortality, its effect is greater for female children. These findings are expected under the assumption that only healthy male fetuses survive to adverse conditions during pregnancy (Trivers and Willard, 1973; Kraemer, 2000). This is consistent with our main hypothesis that in-utero temperature shocks affect sex ratio at birth by mostly killing male fetuses.

The remainder of the paper proceeds as follows. Section 2 presents our contribution to the closely related literature while section 3 describes the conceptual framework which underlines the mechanism behind the impacts of temperature shocks on sex ratio at birth. Sections 4 and 5 present and discuss our data and methods respectively. The findings and robustness checks are presented in section 6. Sections 7 and 8 show lower bound estimation of fetal mortality and discuss mechanisms behind our main results. Section 9 presents an extension of the paper to sex differences infant mortality. We conclude in section 10.

2 Contributions to the Closely Related Literature

Numerous studies have documented short-term impacts of in utero environmental shocks on various birth outcomes, although the focus in this literature is different from ours. For instance, Strand et al. (2011a) show that extreme temperature might induce heat stress in the mother, possibly causing a mix of biological and behavioral responses such as an increase in blood flow, dehydration, changes in food selection, and appetite loss, all of which are associated with the risk of pregnancy loss. Deschênes et al. (2009) find that exposure to extremely hot temperature during pregnancy leads to lower birth weight in the United States. Using the Islamic month of Ramadan as a natural experiment, Almond and Mazumder (2011) examine the impacts of maternal fasting on a set of birth outcomes. Among their results, the authors find that prenatal exposure to Ramadan in the first month of pregnancy reduces the number of male births. Catalano et al. (2008) document that cold ambient temperatures during gestation predict lower secondary sex ratios and longer life span of males in annual birth cohorts composed of Danes, Finns, Norwegians, and Swedes born between 1878 and 1914. Schifano et al. (2016) estimate the effect of exposure to air pollution and ambient temperature on the risk of birth by week of gestation on singleton live births in Rome and Barcelona. However, few studies have investigated the impacts of prenatal temperature shocks in the context of developing countries especially sub-Saharan Africa. Wilde et al. (2017) test whether temperature spikes at conception, in utero, and immediately after birth causally affect long-run educational attainment, literacy, and disability of adults in sub-Saharan Africa. They find that educational attainment and literacy rise for individuals who were conceived during periods of elevated temperatures. Our paper differs from theirs in that we are concerned about prenatal temperatures shocks short-term impacts rather than the long run human capital consequences.

Our paper differs from the aforementioned literature in four important respects. First, few studies have shown how the impacts of ambient prenatal temperature shocks vary by *stage of pregnancy*, especially in the context of *developing countries* as we do for sub-Saharan Africa. In addition, while outcomes such as sex ratio at birth have been examined, fetal death and male-female differences in infant mortality have been less studied. We find that a cold temperature occurring during the first or the third trimester of pregnancy decreases the likelihood of a male birth, but increases male survival in the infant period. This finding is consistent with the assumption that only healthier male fetuses survive to adverse climatic conditions during pregnancy whereas female fetuses survive these conditions regardless of their health. To our knowledge, these results are new. They add to the general literature showing that climate shocks have uneven distributional impacts in different population subgroups. Unlike our analysis, however, this literature has primarily focused on outcomes occurring after birth.

Second, the extant literature examining the consequences of prenatal temperature shocks has primarily documented “average" effects. We show that the effects of these shocks are highly heterogeneous, being larger for older women, higher parity births, and rural residents. Analyzing impact heterogeneity not only shows that prenatal temperature shocks have uneven distributional impacts, but it is also useful to understand some of the important mechanisms through which these shocks affect outcomes.

Third, our paper is one of the few studies that document male-female differences in responses to external shocks. Existing studies have analyzed the impact of ambient total suspended particulate matter (Sanders and Stoecker, 2015), earthquake intensity (Liu et al., 2015), and temperature shocks (Catalano et al., 2008). However, the focus in these studies is somewhat different from ours. Indeed, we provide the first evidence that the differential effects of temperature shocks on male and female fetuses vary by period of gestation. So our focus on the *timing* of these shocks and on how its effect varies for prenatal vs. postnatal outcomes (that is, sex ratio at birth vs. infant mortality) is new.

Finally, we show how it is possible to use our estimated effect of temperature on sex ratio at birth to recover a lower bound of fetal mortality due to change in ambient temperature. This finding highlights the health cost of climate change in the context of sub-Saharan African countries, and can also be viewed as a contribution to the literature on the determinants of child and maternal health in the developing world. This is relevant not just for health policy design, but also for the analysis of the future impact of climate change. Policies focusing on population subgroups with low biological endowments are likely to avert the negative impacts of climatic shocks. Our results imply that these policies should account for stages of fetal development.

3 Conceptual Framework: How Do Temperature Shocks Affect Sex Ratio at Birth?

This section documents the possible channels through which climatic conditions including ambient temperatures (T) influence human sex ratio at birth (SRB). Factors determining the SRB are of two kinds: factors determining the primary sex ratio at conception (PSR) and factors determining sex differentials in intrauterine mortality ($SSIM$) (Chahnazarian, 1988). While the former factors are likely to play an important role in the early pregnancy period (i.e. around the period of conception), the latter factors play a role only after the fetus has been and over the course of the pregnancy. Formally, we can write the following expression:

$$SRB = PSR \times SSIM \tag{1}$$

where SRB is the number of live male births divided by the total number of live births (i.e. the proportion of male births), PSR is the proportion of fetuses that are conceived as male, and

SSIM is the survival rate of males from conception through delivery divided by the survival rate of all babies from conception through delivery. SRB is observable in our dataset, whereas PSR and SSIM are not.

The change in the offspring sex ratio due to a marginal change in ambient temperature (T) is obtained by differentiating equation (1) with respect to temperature as follows:[3]

$$\frac{\partial SRB}{\partial T} = \frac{\partial PSR}{\partial T} SSIM + \frac{\partial SSIM}{\partial T} PSR \tag{2}$$

Temperature may influence primary sex determination by the variable fertilization success of X- and Y- bearing sperm (McLachlan and Storey, 2003). Moreover, there is evidence supporting that ambient temperature and stressful environmental conditions affect the steroid concentrations of ovarian follicles (Wolfenson et al., 2000; De Rensis and Scaramuzzi, 2003), and may also impair sperm mobility and potentially promoting female biased primary sex ratio (Fukuda et al., 1996). To help understand which of these channels drive our results we study how sex ratio at birth is impacted by temperature changes both around and after conception.[4]

The exposure to weather shocks among pregnant mothers can affect their offspring's sex ratio through three potential mechanisms that impact fetus either directly or indirectly through mother's responses. These include: *(i)* biological effect induced by heat stress which might result in several health issues including risk of placenta abruption (He et al., 2018), preterm and stillbirth (Carolan-Olah and Frankowska, 2014; Strand et al., 2011b) or pregnancy loss (Beltran et al., 2014); *(ii)* behavioral mechanism with change in consumption habits (food selection, appetite loss); given the importance of nutrition on maternal health and birth outcomes (Figlio et al., 2009), change in consumption behavior as a result of variation in ambient temperature is therefore fundamental for fetal development; *(iii)* income channel which refers to negative impacts of extreme temperature on agricultural yields and thus household resources. For instance, in rural areas where a significant fraction of income is derived from agriculture, crop yields might change in response to adverse weather shocks. Recent literature documents the relationship between high temperatures and crop yield including Schlenker and Roberts (2009) and Burgess et al. (2011).[5]

[3]For notational simplicity, we ignore the time variable.

[4]We report these point estimates in Table A5 in appendix.

[5]For instance, Schlenker and Roberts (2009) find that temperatures above about 85 $^\circ$ F cause damages to corn and soybeans yields.

4 Data

4.1 Data Sources

Sex ratio at birth and maternal characteristics. We extract data on sex ratio at birth and on maternal characteristics from the Demographic and Health Surveys (DHS). DHS are representative at the national and subnational level, and are comparable across countries and years for most variables. They use a two-stage sampling technique, selecting clusters at the first stage and households at the second stage. The focus in these surveys is primarily on women and their children. We construct a sample of all live births using these surveys. We analyze 85 surveys from 34 countries, obtaining a sample of 1,985,399 live births. All the surveys and the years in which they were conducted are listed in Appendix Table A1. Our primary outcome of interest is an indicator that equals 1 if the child is male, and 0 otherwise. We use the information on place of residence and date of birth for each of the children born to mothers surveyed by the DHS. For each birth, we define the pregnancy period as the nine-month period that precedes the month of birth. The whole pregnancy period is divided in three trimesters. Information on maternal demographic and socioeconomic characteristics include age at delivery, marital status, educational attainment, and a household wealth index.[6] For each child, we also use information on preceding birth interval in months and number of prior children (or child birth other).

Weather variables. Historical weather data are obtained from University of Delaware air temperature and precipitation dataset (UDEL) (Matsuura and Willmott, 2012). UDEL data are gridded at the 0.5×0.5 ° spatial resolution with monthly average measure of temperature and precipitation derived from a large number of stations, both from the Global Historical Climate Network (GHCN) and the archives of Legates and Willmott.[7] The weather dataset extracted from UDEL is then merged to DHS using the child year and month of birth, and mother's place of residence. The merging consists of assigning to each DHS cluster unit — census enumeration area — the weather conditions of the nearest grid cell at the time of pregnancy. In keeping with the literature (Deschênes et al., 2009), we investigate whether temperature effects are non-linear by looking at the impact of average monthly temperature falling into each of five temperature

[6] This index is made available in the DHS data. It aggregates the assets owned by a household using factor analysis. A greater score on the index indicates ownership of more items such as radios or motorcycles. In specifications controlling for this variable, we lose sample size because information on this variable is missing for a large number of observations.

[7] Long-term and geographically representative weather records are not widely available at the daily level in SSA countries.

bins (<18 °C, 18-22 °C, 22-26 °C, 26-30 °C, >30 °C), with 22-26 °C considered as a reference category.[8]

Climate change predictions. To project the future impact of climate change on fetal deaths in our SSA sample, we use the CIMP5 models to obtain the predictions for the future monthly average distribution of temperature and precipitation variables used in our empirical analysis. CIMP5 models provide the most straightforward and scientifically accepted way to project future climate conditions under different RCPs.[9] The CIMP5 suggests that temperature increases for Africa with the high emissions trajectory (i.e. RCP 8.5 scenario) is 1.7°C by the year 2030, 2.7°C by the year 2050, and 4.5°C by the year 2080 (Girvetz et al., 2019), relative to a historical period (1970-2000).

Figure 1 represents the average temperature during pregnancy experienced by individuals in our sample of SSA countries over 1980-2010. It shows that this region of the world has experienced climate change as temperatures tend to increase over time.

4.2 Summary Statistics

Table 1 summarizes the key variables used in our analysis. Our sample period 1980-2010 covers about 1,985,399 live births with 50.8 % of them being male. The average mothers' age at delivery is around 25 years old, with few of them single (12.9%), almost half with no education (43.8%) and 26.3% living in urban areas. Regarding weather conditions during the pregnancy period, individuals were exposed to 23.96 °C and 8.9 cm of average monthly temperature and precipitation, respectively.

Figure 2 depicts histograms of actual (f_a^b) and predicted mid-century (under the RCP8.5 scenario) (f_p^b) distribution of average temperature by bin (b) $\in \{<18$ °C, 18-22 °C, 22-26 °C, 26-30 °C, >30 °C$\}$, respectively. The difference in the height of the bars represents the change in frequency of individuals exposed to a given temperature bin. Figure 2 suggests that most births were exposed to average temperature range between 22 to 30 °C, with few observations for extreme temperatures (i.e. <18 °C and >30 °C). However, regarding the long term predictions, Figure 2 reveals that individuals will be more exposed to hot temperatures rather than to cold temperatures. As projected by most of the climate models, SSA countries considered in our

[8]Later, we show that our estimates of fetal deaths do not vary as we change the reference category bin to 18-22 and 26-30.

[9]Four RCPs were selected and defined by their total radiative forcing (cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter) pathway and level by 2100. The RCPs were chosen to represent a broad range of climate outcomes, based on a literature review, and are neither forecasts nor policy recommendations.

sample are expected to warm in the future with more hot days.

Figure 3 depicts the cross-sectional association between SRB and average temperature during the whole pregnancy period at the macro level of SSA sample countries. We group together for the entire surveyed population and for a given country the average level of temperature observed during pregnancy and the corresponding sex ratio over the entire period 1980-2010. In other words, each dot represents for a given country, aggregate average SRB (ratio of male over total babies) level associated to average temperature experienced during pregnancy. The blue line shows the trend of the relationship between the percentage of births that are male and the monthly average temperature. The shaded area represents the 0.95 confidence interval associated to this correlation.

In the cross-section, extreme cold and hot temperatures during pregnancy are positively correlated with the percentage of male births, whereas moderate temperatures positively affect female births. While this is not evidence of a causal relationship given that there might be confounders at the country level that could contribute to explaining SRB, it is a suggestive evidence that temperature affects the human SRB. Whereas Figure 3 captures the cross-sectional relationship between temperature and SRB at the country level, in Figure 4, we show the same relationship at the individual level. In this chart, for each live birth in our data, we calculate the average temperature during the entire pregnancy. This temperature is then plotted against the probability that the baby is a male. Once again, there are not controls for other potential determinants of child or mother health, so this should be taken as suggestive evidence of a possible relationship between these two variables. Two insights are derived from this chart: First, the association between prenatal average temperature and SRB seems to be non-linear. Second, the graph below is consistent with the conclusion observed at the country level, i.e., extreme temperatures are positively associated with male births, and moderate temperatures are correlated with female births. Indeed, starting from the reference bin $22 - 26$ °C moving either to the hot temperature (right) or to the cold temperature (left) increases the likelihood of a male birth.

5 Methods

5.1 Identification Strategy

The identification strategy exploits the fact that realization of temperature is as good as random once we control for location and time. In order words, after adding month and region of birth fixed effects, the observed variation in monthly temperatures experienced by pregnant mothers is as good as random. These quasi-random temperature shocks reveal the causal impacts of monthly temperature variations on the outcome of interest — gender of birth. A particular feature of this approach is that although our interest is in sex differences in fetal mortality, we only observe live births – that is, we do not observe any of the fetuses that died as a result of adverse climatic conditions. Instead, we infer fetal mortality from differences in the sex ratio at birth for live births conditional on climatic conditions (see Appendix Notes N1).[10]

Our primary specification is non-linear and investigates how SRB varies across temperature bins. Formally, we decompose temperature into each of five bins b, corresponding to $<$ 18 °C, 18-22 °C, 22-26 °C, 26-30 °C and $>$ 30 °C, with 22-26 °C being considered as the reference category.[11] Our main regressor — average temperature experienced on a given period or window of pregnancy including the whole 9-months pregnancy — is a categorical temperature variable.[12] We therefore estimate the following non-linear specification:

$$Male_{ijrt} = \sum_{b} \alpha_b * TEMP^b_{ijrt} + X_j\beta + \mu_r + \delta_m + \epsilon_{ijrt}, \tag{3}$$

where $Male_{ijrt}$ is a binary variable that equals 1 if child i born to mother j in region r, at a given time of pregnancy stage t , is a male, and 0 otherwise. Note that t corresponds to a trimester of pregnancy (first, second and third) or the whole nine month pregnancy period depending on the specification. The region r reflects the DHS cluster unit in which the child was born. DHS cluster units are small geographic areas similar to census enumeration areas. $TEMP^b_{ijrt}$ is an indicator that equals 1 if the average temperature on the corresponding window of pregnancy (first, second or third trimester) is in bin b and 0 otherwise. For instance, if an individual experienced an average temperature of 20 °C during the whole pregnancy period, $TEMP^b_{ijrt}$ equals 1 if b$\in$ 18-22 °C and 0 otherwise. X_j is a set of control variables of mother characteristics such as age at delivery, marital status, birth interval in months, number of prior sons, number of prior children (or child birth other), household's wealth and educational attainment.[13] To account for regional and seasonal variation in activities (employment level,

[10]Figure N1 describes the relative change in fetal death due to an extreme temperature shock for different values of the primary sex ratio.

[11]We choose 22-26 °C as the reference category because the average monthly temperature in our sample is about 23 °C. We are therefore interested in how temperature deviation from this reference category impacts our primary outcome, the SRB.

[12]Much of the recent literature studying the effects of temperature on socio-economic outcomes uses daily or even hourly measures of temperature. In contrast, our paper uses monthly average temperature, since daily temperature observations for SSA are sporadic, more scarce and unreliable than in any other region in the world (see Dell et al. (2014) for a more detailed discussion).

[13]This set of regressors follows Chahnazarian (1988) and controls for socio-economic determinants of human

change in climatic conditions, etc.) specific to each region, we add region and month of birth fixed effects, μ_r and δ_m, respectively. Finally, the error term, ϵ_{ijrt}, represents unobserved shocks and is assumed to be uncorrelated with the regressor of interest.

Later, as a robustness check, we model a polynomial specification of the relationship between SRB and a continuous measure of temperature experienced on a whole gestational period. Specifically, the functional form includes quadratic terms of temperature:

$$Male_{ijrt} = f(TEMP_{ijrt}) + X_j\beta + \mu_r + \delta_m + \epsilon_{ijrt} \tag{4}$$

In addition to the above specification in equation 4, we consider changes from our preferred specification (equation 3) as alternative specifications. One concern with our main specification is that there are unobserved mother characteristics that might be correlated with sex ratio, and that mothers are heterogeneous in their ability to time pregnancies. To address this potential source of confounding, we run a specification that includes mother fixed effects. Identification in this model is derived from variation in temperature exposure across siblings born to the same mother, and addresses potential concerns related to heterogeneous timing of births across mothers with different characteristics. Another threat to causal inference is that other weather indicators, especially rainfall variation, could interplay with our results. We run our main specification of the impact of temperature shocks on SRB controlling for average precipitation level, given that the latter is a key determinant of agricultural yields and susceptible to significantly affect the likelihood of infectious diseases with negative impacts on mother's health. We also include region and both month and year of birth fixed effects to capture regional changes from year to year rather than monthly frequency, susceptible to impact birth outcomes such as investments in public health infrastructures and modern technologies in pregnancy follow-up.

Second, our setting assumes that place of birth is the same as the place of residence, which might not be the case as women might move after conception or before birth. As a result our estimates can be biased since we imperfectly measure the exposure to temperature shocks. To check the robustness of our results, we run our preferred specification on a sub-sample of women who reported they have been living in the same place for at least 10 years.

As an attempt to study possible mechanisms through which temperatures affect sex ratio, in section 8, we study heterogeneity in temperature effects. We include interaction terms between temperature variables and mother's characteristics such as age at birth, birth order, and education. We are uncertain whether or not the learning process by mother from birth to

sex ratio at birth (SRB).

birth dominates over her health status which declines with age and with the number of prior children born. We test these two channels by estimating heterogeneous treatment effects.

In an extension, in section 9, we further explore the impacts of temperature shock on the infant mortality (mortality occurring within the first year after birth) for each sex category. Looking at the differential impact of temperature on infant mortality by sex serves to validate our argument of fetal mortality as a main driver of offspring sex ratio. Indeed, if we believe that male fetuses are more fragile than female fetuses (Kraemer, 2000), we expect to find a greater effect of temperature shocks on females after birth as sex-biased in utero mortality selection implies that among fetuses that survive to birth, males are healthier than females.

6 Main Results

6.1 Impact of Extreme Temperature on Sex Ratio at Birth

We find that cold temperature at the time of pregnancy is negatively correlated with a male birth. Table 2 reports our main estimates of equation 3. Each column refers to the estimation of equation 3 for a given trimester of pregnancy as well as the whole gestational period. All regressions include region and month of birth fixed effects, and control for mother's characteristics. The latter includes mother's age at delivery, marital status, birth interval in month, number of prior children (or child birth order), and educational attainment.[14] The coefficient estimates are interpreted relative to the reference temperature bin 22-26 °C. It follows that, irrespective of the trimester of pregnancy, cold temperatures decrease the likelihood of a male birth. For instance, relative to ambient temperature in 22-26 °C, an average temperature below 18 °C experienced during pregnancy decreases by 0.712 percentage points the probability of a male birth, which is a substantial effect.

The effects of hot temperatures on male birth depend on the trimester of pregnancy. Our estimates show that, relative to an average temperature in 22-26 °C, a mean temperature above 30 °C experienced in the first and third trimester of pregnancy decreases the probability of a female birth by 0.438 and 0.484 percentage points, respectively. The magnitudes of the effects are statistically significant and consistent across trimesters. Figure A1 represents graphically these point estimates of the effects of mean temperature on a male birth by trimester of pregnancy. The shaded areas represent the 95 percent confidence interval associated to these point

[14] Our results do not vary as we remove those mother's controls. In other words, they are not likely to be driven by selection on unobservables.

estimates.

These point estimates are obtained with a dummy indicator for whether the entire pregnancy had an average temperature in a certain bin. One concern with this way of measuring average temperature during pregnancy is that differences in distribution of temperatures across the 9-month gestational period may influence mothers differently. For instance, an average temperature of 20 °C during pregnancy that results from a 20 °C temperature in each month of the 9-month of pregnancy period has a different effect than an average temperature of 20 °C obtained from a distribution in which temperature varies from one month to another during the pregnancy period. To account for this possibility, we use a count variable of the number of months where temperature belongs to a specific bin. Table A4 reports results of this specification where we estimate equation 3 in which we replace our main regressor by a count variable of the number of months on a given window of pregnancy, where temperature falls in a specific bin. Our findings are consistent with the main results of this paper solely when we consider the effects during the first trimester of pregnancy as shown in column (2). We have two plausible explanations to that: First, this result implies that first trimester appears to be the most critical window of gestational period, consistent with the biology literature. Second, this finding could be due to the fact that most individuals from our sample were less exposed to average temperature in extreme cold and hot bins in the rest of trimesters of gestation.

Our estimates are consistent with those from prior studies, which indicate that cold temperatures during pregnancy negatively affect the probability of a male birth (Catalano et al., 2008). In the context of developing countries including SSA, it is well established that cold temperatures favour the likelihood of infectious diseases such as malaria which is harmful for individuals especially pregnant women (Council et al., 2001; Fares, 2013). According to Trivers and Willard (1973), these prenatal adverse conditions induced by cold temperatures should be more crucial for male fetuses compared to female fetuses. Our findings are supportive to the latter hypothesis. Moreover, the effect we find persists over the different stages of pregnancy. Since primary sex formation occurs during the first trimester, this evidence suggests that the effect of temperature operates primarily through sex selective intrauterine mortality, rather than primary sex selection.

What could explain mortality in females when it is hot? Or said differently, why does the occurrence of male births increase with higher temperature in SSA? Although we do not have direct answer to this question, our explanation is based on the fact that people in tropical countries are familiar to average hot temperature. It follows that, cold temperatures, more unusual, are perceived as a negative shock to individual health. Therefore under the assumption that negative environmental conditions are associated with cold temperatures, our results are in line with Trivers and Willard (1973) and provide evidence that with warmer expected temperatures in the future, the sex ratio at birth will be biased towards males.

6.2 Robustness Checks

6.2.1 Non-linearity in the Effect of Temperature

Our main specification uses a non-parametric binning approach to allow for non-linearity in the effect of temperature on the probability of being born male in equation 3. In this section, we estimate equation 4, which allows temperature to non-linearly affect SRB using a polynomial specification. For ease of presentation, we present these estimates graphically. Figure 4 in section 4 suggests a quadratic functional form of the relationship between temperature and the probability of a male birth. We therefore regress a binary indicator for male birth on the level and the quadratic term of the average temperature experienced during pregnancy minus 22 °C . The coefficients of interest are therefore interpreted as marginal effects of relative average temperature (compared to 22 °C) on the probability of having a male birth. This effect is graphically represented by Figure 5.

Results are consistent with those obtained with the temperature bins model. Although the point estimates are percentage point higher than those obtained with the binned model, the shape of the relationship stays constant with hot temperatures tending to favour male birth.

6.2.2 Alternative Specifications

We replicate our preferred specification, this time using the average temperature of the whole period of pregnancy as the main predictor, and adding controls such as rainfall together with different fixed effects as in Table 2. Table 3 summarizes our results. For ease of analysis, we estimate our main specification in column (1). We then consider different alternative specifications presented in columns (2)-(4) where each of them differ from our preferred specification in column (1) by a given set of controls and/or fixed effects.

Column (2) adds to our preferred specification mother's fixed effect. This variable controls for the possibility that there might be unobserved mother's characteristics correlated to sex ratio and pregnancy timing, given that mothers are heterogeneous in their ability to time pregnancies. Estimates in column (2) show that cold temperature negatively affects the likelihood of male birth. Specifically, an average temperature below 18 °C experienced during pregnancy, decreases the probability of male birth by 0.512 percentage points.

Column (3) accounts for the possibility that regional changes are more likely to happen from year to year rather than on a monthly basis. It therefore controls for year of birth fixed effects. Our findings are consistent with those obtained from the main specification.

Finally, Column (4) controls for average precipitation during pregnancy. Findings are consistent with those from the main specification and suggest that despite variation in rainfall, cold temperatures still have an economically and statistically significant impact on the likelihood of male birth.

6.2.3 Addressing Migration Concerns

One potential source of bias in our estimates is migration that occurs after conception but before birth. Since we only observe the place of residence and not the place of birth nor the place of conception, so far, we have assumed that they are all the same.[15] If this is not the case, one cannot be sure that the individuals in our sample were exposed to the realized temperatures in their region of birth. In order to support the robustness of our results, we interact our main regressor — average temperature during pregnancy — with a dummy variable equal to 1 if the mother has lived at least 10 years at the place of residence, and 0 otherwise. Figure 6 reveals that results are consistent with those obtained in Table 2. Indeed, irrespective of the number of years a typical mother has spent at the place of residence, a cold weather shock decreases the probability of a male birth whereas a hot weather reduces the probability of a female birth.

7 Long-term Effect of Climate Change on Fetal Mortality

This section shows how to recover, from our reduced-form model, a lower bound of fetal mortality (for males and females pooled together) due to change in average temperature. We consider fetal mortality estimation as a lower bound given that our empirical setting only captures the unbalanced effect of temperature shock on a given sex; that is, if the shock affects identically male and female fetuses, we do not measure it. In others words, deviation of point estimates from 0 indicates mortality in one sex relative to the other due to ambient temperature. Therefore, it is more likely that our setting measures a lower bound of the true impact. In keeping with the literature (Zhang et al., 2018), we derive a lower bound of fetal mortality due to vari-

[15] See Wilde et al. (2017) for similar assumptions.

ation in current temperature as a weighted summation of all marginal effects observed during the whole pregnancy period. Following column (1) of Table 2, estimates are associated to each of our five temperature bins. To derive the lower bound of fetal deaths, we weighted each estimates to the corresponding actual temperatures bins distribution f_a^b experienced during the entire pregnancy period. Given that each point estimate corresponds to the marginal effect of a typical temperature bin on the likelihood of a male birth, adding these point estimates weighted by the distribution of temperature bins allows to derive an estimation of a lower bound of fetal mortality. Formally, the lower bound is obtained from equation 5 as follows:

$$LowerBound = \sum_b f_a^b \mid \hat{\alpha}_b \mid, \tag{5}$$

where f_a^b indicates the actual distribution of average monthly temperature by bin. Solving equation 5 leads to 200 fetal deaths per 100,000 live births in our SSA sample due to actual distribution of temperature.

To predict the effect of climate change on fetal mortality and sex ratio at birth (SRB) by mid-century (2050) in our SSA sample, we use the regression coefficient estimates for each temperature bin variable from equation 3. We then calculate the predicted difference in each temperature bin as $(f_p^b - f_a^b)$ as projected by CIMP5 models under RCP 8.5 scenario by 2050. These predicted differences are then multiplied by the relevant estimated regression coefficient to infer the impacts of climate change on fetal mortality and SRB for individuals from our SSA sample. Standard errors are calculated using the delta method.[16] It is important to explain some of the assumptions behind these climate predictions. While we allow climate change to affect the distribution of weather variables such as temperature and precipitation, we hold all other determinants of SRB constant. This includes, among others, change in socio-demographic characteristics, technology improvement related to maternal health, fertility rate dynamics. Finally, our calculations suggest that fetal mortality is projected to be around 400 deaths per 100,000 live births by mid-century in our SSA sample. We summarize our estimations of lower bound of fetal mortality due to temperature shocks as well as the corresponding SRB in Table 4.

As we acknowledge, one concern is that our estimates might depend on the chosen reference temperature bin. To address this treat to our results, we repeat this exercise and report the

[16] The delta method is a simple and widely used tool to derive the asymptotic distribution of nonlinear functional of an estimator. The essence of the delta method is a first order Taylor expansion of the functional.

actual and predicted estimations of fetal mortality by temperature bin. As shown in Table A5 in appendix, our results do not vary with reference temperature bin.

8 Mechanisms: Heterogeneous Effects of Temperature Shocks

In this section we explore the potential channels through which prenatal ambient temperatures affect fetal outcomes. While it is beyond the scope of this study, and beyond the limitations of the available data, to disentangle all possible mechanisms, we can use heterogeneous treatment impacts to help reduce the set of plausible explanations and to understand some possible policy implications regarding the mitigation of climate shocks.

Our heterogeneity in the impacts of average temperature during pregnancy underlines two possible channels which both affect mother's behavior and health. The direct effects that capture the parental experience analyzes how impacts vary with mother's education, age at delivery and child birth order. Through these heterogeneity effects we aim to test whether or not, mother's learning process and adaptation to climate shocks dominate over the health status, as the later is supposed to change over time.

Temperature can also affect mother indirectly via the effects of agricultural yields in rural areas and through the quality of health infrastructures and technology specific to maternal follow-up. These two ideas (change in income agriculture and quality of health infrastructure) are examined using DHS variable individual place of residence, either rural or urban zone.

To test these heterogeneous treatments, we estimate the non-linear version of equation 1, considering four intrinsic characteristics of the mother — education, age at delivery, birth order, and place of residence (urban vs rural). Formally, we run the following model:

$$Male_{ijrt} = \sum_{b} \alpha_b * TEMP^{b}_{ijrt} \times H + X_j\beta + \mu_{rm} + \epsilon_{ijrt} \tag{6}$$

where H $\in \Big\{$ education; age at delivery; birth order; place of residence. $\Big\}$

Results are reported in Table 5. The dependent variable is an indicator equal to 1 if the sex at birth is male and 0 otherwise. This table shows temperature heterogeneous effects for the whole pregnancy period — estimated coefficients with standard errors in the brackets. Heterogeneous characteristics consider mother's education, age at delivery, child's birth order, and place of residence (urban vs. rural). The omitted categories considered are mother having education, and living in rural area for variables education and place of residence (urban or rural), respectively. We run our preferred specification with region and month of birth fixed effects and controls for mother's characteristics.

Overall, our heterogeneous results indicate that age at delivery, child birth order, and place of residence are important determinants of the sensitivity of fetus to high and low temperatures. While the estimates show that the effect of temperature of the probability of a male birth does not vary significantly by education, we find that it is larger for rural women compared to their urban counterparts. More precisely, unlike in rural areas, a cold shock in urban areas observed during pregnancy is more likely to increase a male birth. The previous result on the effect of temperature shock on the probability of a male birth in urban areas is intuitive. Indeed, in most SSA countries, urban areas have a level of development that offers better health infrastructures and a better quality of life compared to poorer rural areas. This difference in the level of development therefore affects the quality of health care and prenatal supervision enjoyed by women living in urban areas relative to those living in rural ones. The main result in this paper indicates that cold (respectively, hot) average temperatures experienced during pregnancy reduce the likelihood of a male (respectively, female) birth. This heterogeneous result thus indicates that the negative effect of cold (respectively, hot) average temperatures shock on a male (respectively, female) birth is mitigated in urban areas endowed with better infrastructures compared to rural areas.

Relative to parental experience to adapt and learn from climate shocks, our results are not conclusive. Indeed, younger mother with few births are less affected by temperature shocks compared to their counterparts. This result is consistent with the biological literature which states that age and multiple births are both risk factors susceptible to reduce the probability to carry fetus through delivery.

9 An Extension: Sex-specific Effect of Temperature on infant Mortality

So far, we have shown that in utero average temperature affects the offspring sex ratio and that this effect differs across stages of pregnancy. We have also examined how these effects vary with mother's characteristics and how estimates can be used to recover a lower bound of climate related fetal death rate. In this section, we extend the analysis to infant death, which lends additional credence to our argument that temperature shocks affect sex ratio at birth through fetal death. The infant period —the period between birth and the age of one year

—is a natural extension of the period during which critical child development continues. In addition, before the age of five, death rates are the highest during the infant period (Pongou et al. (2019)).

In analyzing the effect of in utero temperature shocks on infant mortality, we distinguish between male and female children. In regions where females are not discriminated against in the allocation of foods and other health resources, death rates are higher for boys compared to girls due to sex differences in prenatal and biological factors (Pongou (2013), Pongou (2015), Pongou et al. (2017), Pongou (2020)). If prenatal temperature shocks have a greater effect on weaker male fetuses than on weaker female fetuses, then fetuses that survive to adverse prenatal conditions will produce stronger boys than girls. If so, male-female differences in the effects of prenatal temperature shocks on infant mortality will be in the opposite direction to their effects on sex ratio at birth.

The findings are reported in Table 6. All regressions are clustered at the mother level and control for child birth order. We consider the average temperature in each temperature bin experienced during the whole 9-month pregnancy period. The coefficient estimates are interpreted relative to a reference temperature bin, 22-26 °C, with standard errors in brackets. We find that a cold temperature shock experienced during pregnancy decreases the probability of infant mortality. This effect is larger for boys than for girls, and is opposite to what happens in utero, as a cold temperature shock reduces sex ratio at birth, meaning that its effect on fetal mortality is greater for male fetuses than for female fetuses. Our results therefore indicate that poor conditions in utero are more harmful for males relatives to females (Kraemer, 2000).

While Table 6 reports non-linear estimates of the effects of temperature in each bin averaged over the whole 9-month pregnancy period, Table 2 breaks the analysis by trimester of pregnancy. Our findings show that cold temperatures in the first trimester only reduce infant mortality (Panel A). In the first trimester, an average temperature below 18 °C decreases mortality more in girls than in boys, and an average temperature in the range 18-22 °C decreases mortality more in boys than in girls (Panels B and C). A cold temperature shock occurring in the second trimester of pregnancy increases infant mortality. The effect larger for boys than for girls for average temperature below 18 °C, and larger for girls for average temperature in the range 18-22 °C (Panels B and C). Temperature shocks occurring in the third trimester have no significant effect in general (Panel A), except in girls in which they increase mortality (Panels B and C). Our results are somewhat consistent with the notion that only healthy males are likely to survive to fetal insults, whereas the survival of female fetuses depends less on their health.

10 Conclusion

This study provides new causal evidence on how the timing of prenatal climate shocks affects early-life human capital formation. We achieve a threefold goal. First, we estimate the direct impact of average temperature during pregnancy on sex ratio at birth, and document for the first time how this effect varies over the course of pregnancy. Adjustment in the sex ratio at birth in response to adverse climatic shocks is used as an alternative measure of fetal mortality. Second, using our estimated effects in combination with a climate model, we are able to uncover a lower bound of the actual and long-term impacts of climate change on fetal mortality (for male and female fetuses pooled together). Third, as an extension of our analysis, we analyze the sex-specific impact of prenatal temperature on infant mortality. In addition to these analyses, we provide evidence for the heterogeneous effects of temperature shocks, therefore documenting some key mechanisms through which these shocks operate.

Our analyses use Demographic and Health Surveys (DHS) from sub-Saharan African countries and historical gridded monthly data on temperature and precipitation from University of Delaware precipitation dataset (UDEL). Our main findings show that male and female fetuses are affected differently by adverse environmental conditions, and that these effects vary with gestation period. Irrespective of the trimester of pregnancy, a cold temperature shock decreases the likelihood of a male birth. For instance, relative to ambient temperature in 22-26 °C, an average temperature below 18 °C experienced during pregnancy decreases by 0.712 percentage points the probability of a male birth. These findings are consistent with those obtained in developed countries, where adverse climatic conditions such as ambient colder temperature during pregnancy is more harmful for males relative to females (Catalano et al., 2008). In our analysis, we find that the effects of prenatal temperature shocks are non-linear, being more pronounced in the first and third trimesters of pregnancy. They are also highly heterogeneous, being larger for older women, higher parity births, and rural residents. We further provide a lower bound estimate of fetal mortality of around 200 fetal deaths per 100,000 live births in response to actual cold and hot temperature experienced during the pregnancy period. Moreover, using a well-known climate model, we derive the future predictions of fetal deaths of around 400 per 100,000 live births by 2050 throughout sub-Saharan Africa. Finally, we extend our analysis to infant mortality, finding that, in contrast to their differential effects on fetal mortality, prenatal temperature shocks increase infant mortality more for girls than for boys, which suggests that only healthier male fetuses survive to fetal insults.

Our findings have important policy implications. Estimates of change in fetal death, sex ratio at birth, and infant mortality are relevant as these outcomes affect future social movements such as marriage, crime, and the labor market. Our analysis can also inform public policies designed to prevent pregnant women from the adverse effects of climate shocks. It implies that such policies should account for stages of fetal development.

References

Abramitzky, R., Delavande, A., and Vasconcelos, L. (2011). Marrying up: the role of sex ratio in assortative matching. *American W: Applied Economics*, 3(3):124–57.

Almond, D., Currie, J., and Duque, V. (2018). Childhood circumstances and adult outcomes: Act ii. *Journal of Economic Literature*, 56(4):1360–1446.

Almond, D. and Mazumder, B. (2011). Health capital and the prenatal environment: the effect of ramadan observance during pregnancy. *American Economic Journal: Applied Economics*, 3(4):56–85.

Amuedo-Dorantes, C. and Grossbard, S. (2007). Cohort-level sex ratio effects on women's labor force participation. *Review of Economics of the Household*, 5(3):249–278.

Angrist, J. (2002). How do sex ratios affect marriage and labor markets? evidence from america's second generation. *The Quarterly Journal of Economics*, 117(3):997–1038.

Barker, D. J. (1997). The fetal origins of coronary heart disease. *Acta Paediatrica*, 86(S422):78–82.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.

Barreca, A., Deschenes, O., and Guldi, M. (2018). Maybe next month? temperature shocks and dynamic adjustments in birth rates. *Demography*, 55(4):1269–1293.

Beltran, A. J., Wu, J., and Laurent, O. (2014). Associations of meteorology with adverse pregnancy outcomes: a systematic review of preeclampsia, preterm birth and birth weight. *International journal of environmental research and public health*, 11(1):91–172.

Brown, M. E. and Funk, C. C. (2008). Food security under climate change. *Science*, 319(5863):580–581.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2011). Weather and death in india. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript*, 19.

Cameron, L., Meng, X., and Zhang, D. (2019). China's sex ratio and crime: Behavioural change or financial necessity? *The Economic Journal*, 129(618):790–820.

Carleton, T., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., Kopp, R. E., McCusker, K., Nath, I., et al. (2018). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits.

Carolan-Olah, M. and Frankowska, D. (2014). High environmental temperature and preterm birth: a review of the evidence. *Midwifery*, 30(1):50–59.

Catalano, R., Bruckner, T., and Smith, K. R. (2008). Ambient temperature predicts sex ratios and male longevity. *Proceedings of the National Academy of Sciences*, 105(6):2244–2247.

Chahnazarian, A. (1988). Determinants of the sex ratio at birth: review of recent literature. *Social biology*, 35(3-4):214–235.

Council, N. R. et al. (2001). *Under the weather: climate, ecosystems, and infectious disease*. National Academies Press.

De Rensis, F. and Scaramuzzi, R. J. (2003). Heat stress and seasonal effects on reproduction in the dairy cow—a review. *Theriogenology*, 60(6):1139–1151.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature*, 52(3):740–98.

DESA, U. (2015). United nations department of economic and social affairs, population division. world population prospects: The 2015 revision, key findings and advance tables. In *Technical Report*. Working Paper No. ESA/P/WP. 241.

Deschênes, O., Greenstone, M., and Guryan, J. (2009). Climate change and birth weight. *American Economic Review*, 99(2):211–17.

Dessy, S., Marchetta, F., Pongou, R., and Tiberti, L. (2019). Fertility after the drought: Theory and evidence from madagascar.

Du, Q. and Wei, S.-J. (2011). *Sex ratios and exchange rates*. National Bureau of Economic Research.

Edlund, L., Li, H., Yi, J., and Zhang, J. (2013). Sex ratios and crime: Evidence from china. *Review of Economics and Statistics*, 95(5):1520–1534.

Fares, A. (2013). Factors influencing the seasonal patterns of infectious diseases. *International journal of preventive medicine*, 4(2):128.

Figlio, D., Hamersma, S., and Roth, J. (2009). Does prenatal wic participation improve birth outcomes? new evidence from florida. *Journal of Public Economics*, 93(1-2):235–245.

Fukuda, M., Fukuda, K., Shimizu, T., Yomura, W., and Shimizu, S. (1996). Kobe earthquake and reduced sperm motility. *Human reproduction*, 11(6):1244–1246.

Girvetz, E., Ramirez-Villegas, J., Claessens, L., Lamanna, C., Navarro-Racines, C., Nowak, A., Thornton, P., and Rosenstock, T. S. (2019). Future climate projections in africa: where are we headed? In *The Climate-Smart Agriculture Papers*, pages 15–27. Springer.

Grace, K. (2017). Considering climate in studies of fertility and reproductive health in poor countries. *Nature climate change*, 7(7):479.

He, S., Kosatsky, T., Smargiassi, A., Bilodeau-Bertrand, M., and Auger, N. (2018). Heat and pregnancy-related emergencies: Risk of placental abruption during hot weather. *Environment international*, 111:295–300.

Hertel, T. W. (2016). Food security under climate change. *Nature Climate Change*, 6:10–13.

Isen, A., Rossin-Slater, M., and Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, 114(51):13447–13452.

Jukic, A. M., Baird, D. D., Weinberg, C. R., McConnaughey, D. R., and Wilcox, A. J. (2013). Length of human pregnancy and contributors to its natural variation. *Human reproduction*, 28(10):2848–2855.

Kang, Y. and Pongou, R. (2019). Sex ratios, sexual infidelity, and sexual diseases: Evidence from the united kingdom. *Sexual Infidelity, and Sexual Diseases: Evidence From the United Kingdom (April 18, 2019).*

Knobel, R. and Holditch-Davis, D. (2007). Thermoregulation and heat loss prevention after birth and during neonatal intensive-care unit stabilization of extremely low-birthweight infants. *Journal of Obstetric, Gynecologic, & Neonatal Nursing*, 36(3):280–287.

Kraemer, S. (2000). The fragile male. *Bmj*, 321(7276):1609–1612.

Liu, E. M., Liu, J.-T., and Tseng, T.-Y. H. (2015). The impact of a natural disaster on the incidence of fetal losses and pregnancy outcomes. *Draft, July.*

Matsuura, K. and Willmott, C. (2012). Terrestrial air temperature and precipitation: 1900-2010 gridded monthly time series.

McLachlan, J. C. and Storey, H. (2003). Hot male: can sex in humans be modified by temperature? *Journal of theoretical biology*, 222(1):71–72.

Orzack, S. H., Stubblefield, J. W., Akmaev, V. R., Colls, P., Munné, S., Scholl, T., Steinsaltz, D., and Zuckerman, J. E. (2015). The human sex ratio from conception to birth. *Proceedings of the National Academy of Sciences*, 112(16):E2102–E2111.

Pongou, R. (2013). Why is infant mortality higher in boys than in girls? a new hypothesis based on preconception environment and evidence from a large sample of twins. *Demography*, 50(2):421–444.

Pongou, R. (2015). Sex differences in early-age mortality: The preconception origins hypothesis. *Demography*, 52(6):2053–2056.

Pongou, R. (2020). Is excess (fe)male mortality caused by the prenatal environment, child biology, or parental discrimination? new evidence from male-female twins. *Department of Economics, University of Ottawa, Working Paper*, 2008E.

Pongou, R., Kuate Defo, B., and Tsala Dimbuene, Z. (2017). Excess male infant mortality: The gene-institution interactions. *American Economic Review*, 107(5):541–45.

Pongou, R., Shapiro, D., and Tenikue, M. (2019). Mortality convergence of twins and singletons in sub-saharan africa. *Demographic Research*, 41:1047–1058.

Sanders, N. J. and Stoecker, C. (2015). Where have all the young men gone? using sex ratios to measure fetal death rates. *Journal of health economics*, 41:30–45.

Schifano, P., Asta, F., Dadvand, P., Davoli, M., Basagana, X., and Michelozzi, P. (2016). Heat and air pollution exposure as triggers of delivery: a survival analysis of population-based pregnancy cohorts in rome and barcelona. *Environment international*, 88:153–159.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Strand, L. B., Barnett, A. G., and Tong, S. (2011a). The influence of season and ambient temperature on birth outcomes: a review of the epidemiological literature. *Environmental research*, 111(3):451–462.

Strand, L. B., Barnett, A. G., and Tong, S. (2011b). Maternal exposure to ambient temperature and the risks of preterm birth and stillbirth in brisbane, australia. *American journal of epidemiology*, 175(2):99–107.

Trivers, R. L. and Willard, D. E. (1973). Natural selection of parental ability to vary the sex ratio of offspring. *Science*, 179(4068):90–92.

Wei, S.-J. and Zhang, X. (2011). Sex ratios, entrepreneurship, and economic growth in the people's republic of china. Technical report, National Bureau of Economic Research.

Wilde, J., Apouey, B. H., and Jung, T. (2017). The effect of ambient temperature shocks during conception and early pregnancy on later life outcomes. *European Economic Review*, 97:87–107.

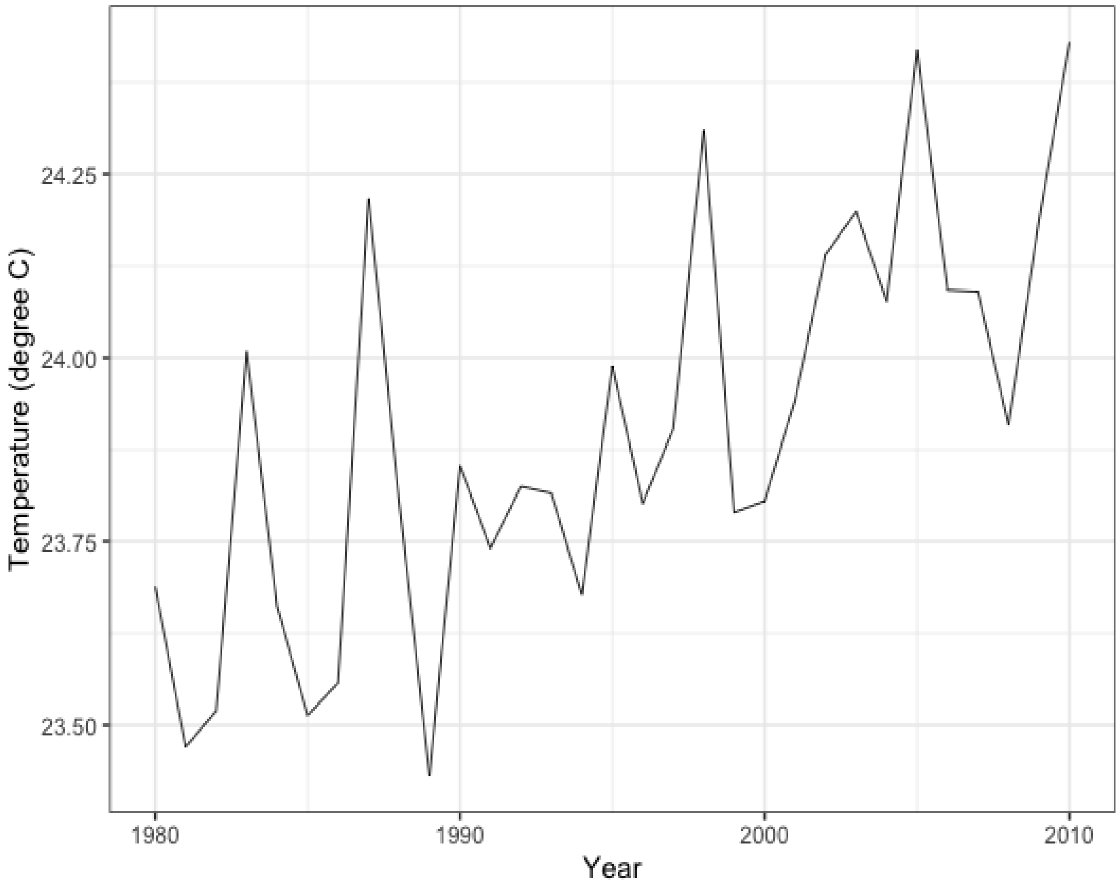
Wolfenson, D., Roth, Z., and Meidan, R. (2000). Impaired reproduction in heat-stressed cattle: basic and applied aspects. *Animal reproduction science*, 60:535–547.

Young, J. B. (2002). Programming of sympathoadrenal function. *Trends in Endocrinology & Metabolism*, 13(9):381–385.

Zhang, P., Deschenes, O., Meng, K., and Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1–17.

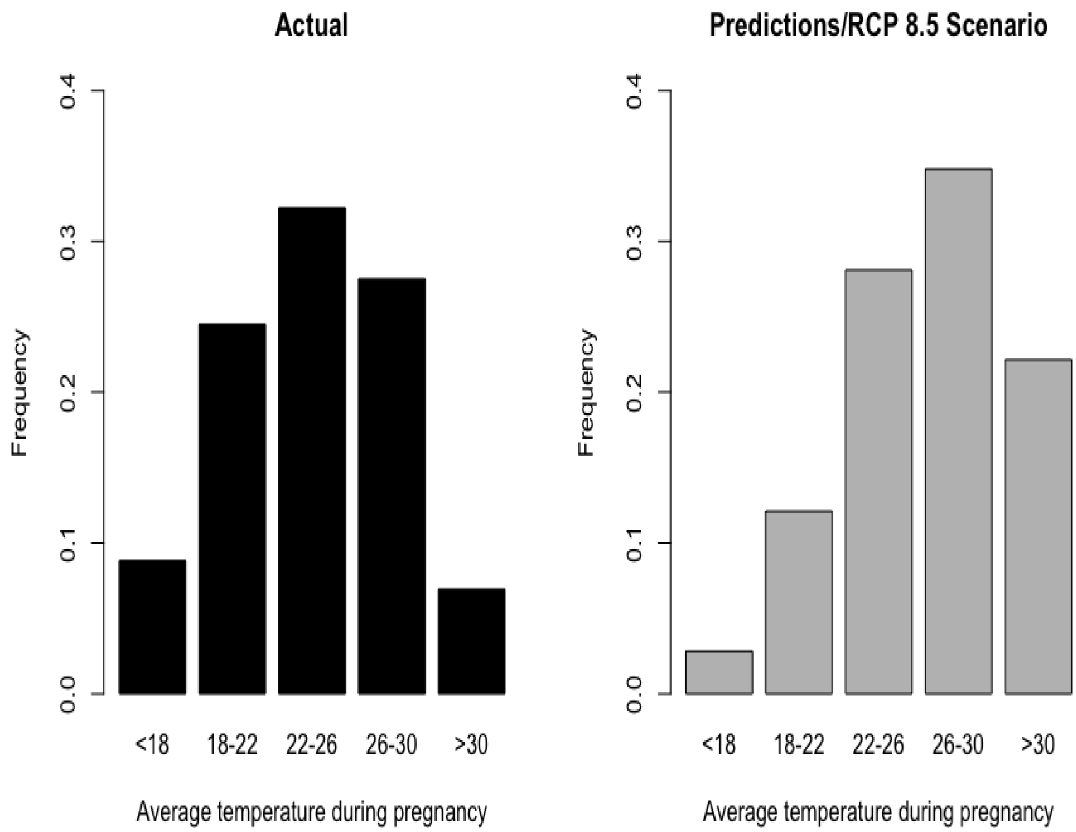
Tables and Figures

Figure 1: Average temperature during pregnancy in our sample of SSA countries over 1980-2010



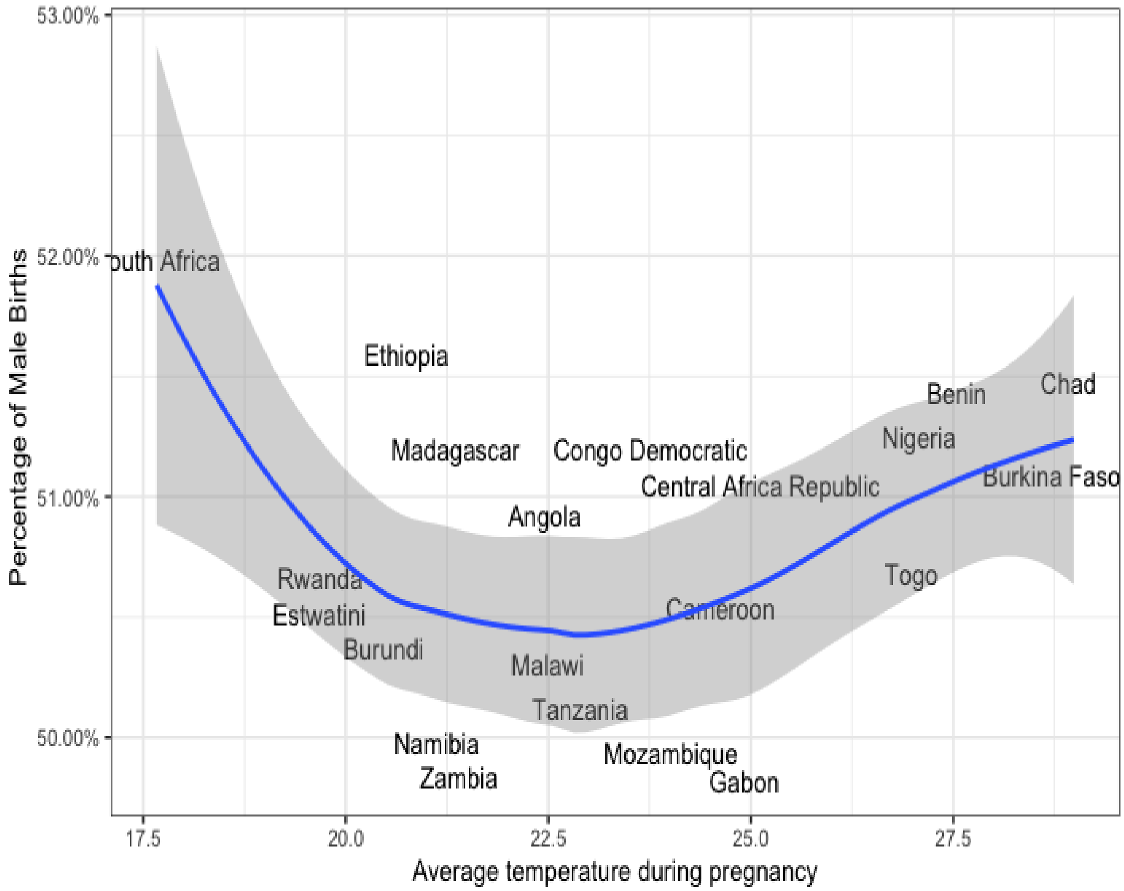
Notes: The figure above plots the change in average temperature experienced by individuals during their 9-month pregnancy period over 1980-2010.

Figure 2: Distribution of actual and predicted monthly average temperature bins



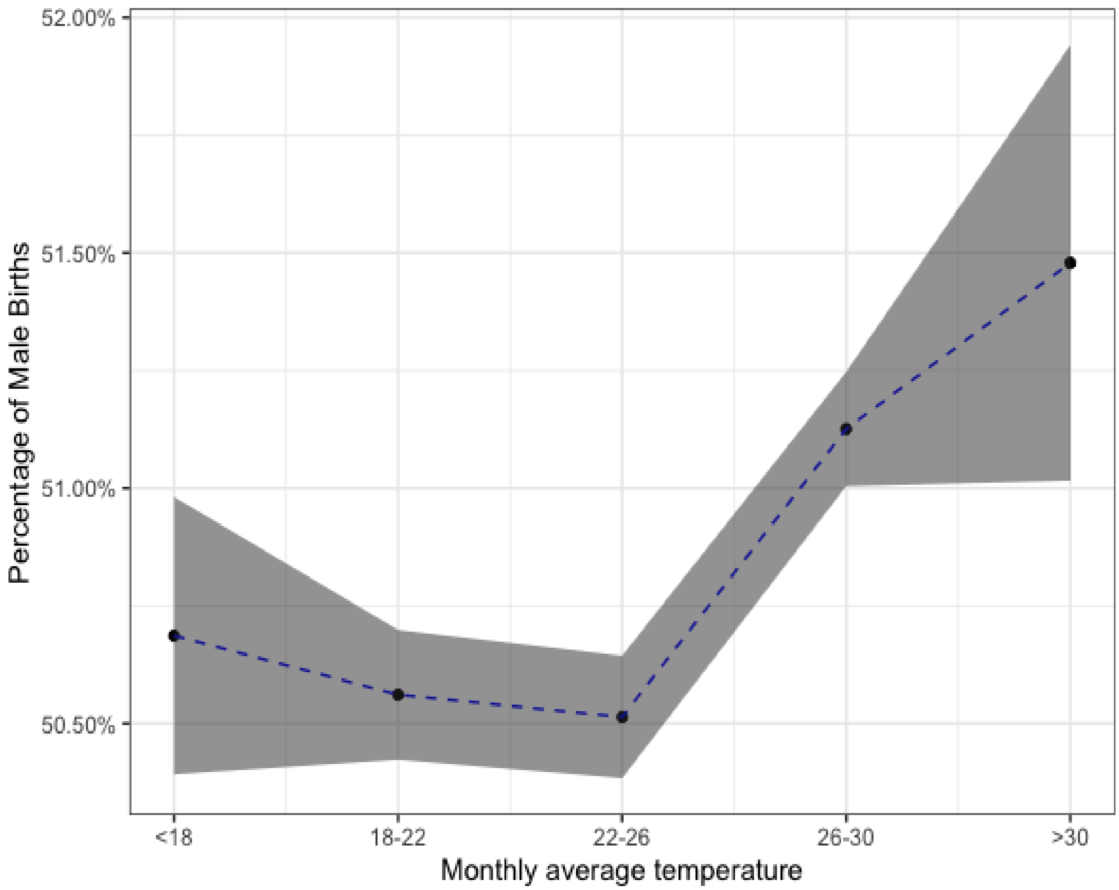
Notes: The figure above plots the actual and long-term predictions of monthly average temperatures. The projections of future temperature are obtained from CIMP5 models under the RCP 8.5 scenario. This model projects a change of 2.7°C in temperature by 2050, relative to a historical period (1970-2000).

Figure 3: Country-level percentage of male births and temperature over the period 1980-2010



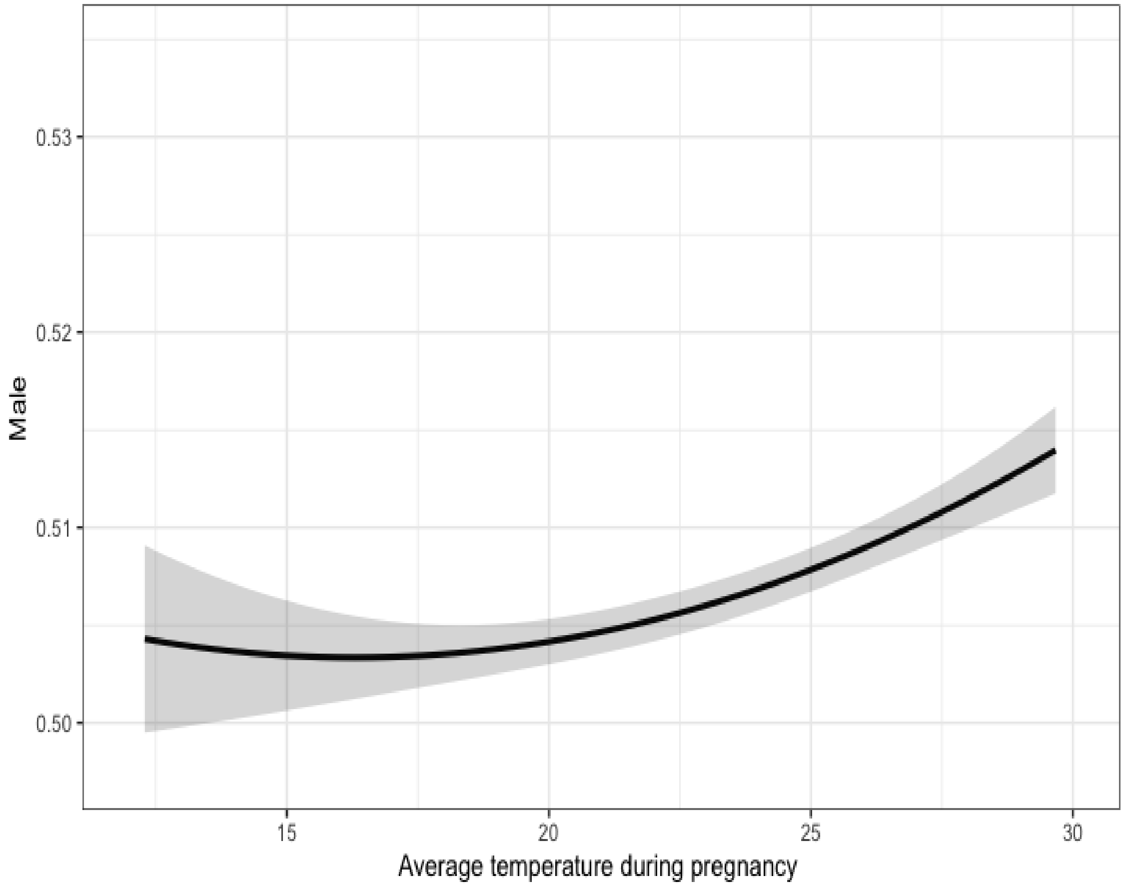
Notes: The figure above is obtained from DHS data on live births. We group these observations by country for a sample period 1980-2010. We represent for a given country aggregate average SRB (ratio of male over total live births) level associated to average temperature experienced during pregnancy. The blue line shows the trend of the relationship between the percentage of births that are male and the monthly average temperature. The shaded area represents the 0.95 confidence interval associated to this correlation.

Figure 4: Percentage of male births by temperature bins during gestational period



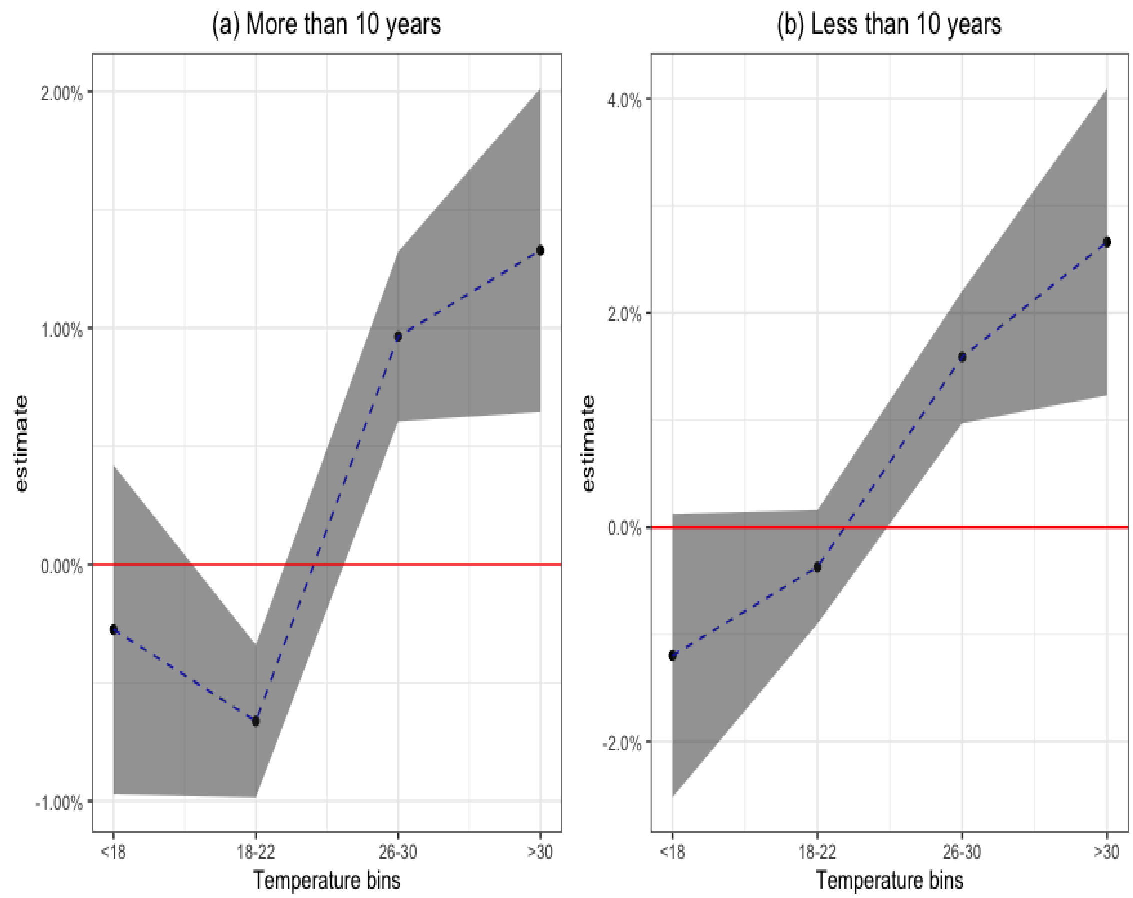
Notes: The figure above is obtained from DHS data on a sample of live births. We aggregate temperature bins during the gestational period for the whole sample period 1980-2010. This chart shows the association between male births and temperature bins with 22-26 °C as reference category. Shaded area represents 0.95 confidence interval. Roughly, it appears a non-linear relationship between temperature and male births.

Figure 5: Temperature effect on male birth using a quadratic model



Notes: The figure above represents a quadratic polynomial functional form of the relationship between average temperature during the pregnancy period and probability of male birth. The coefficient estimates represent the marginal effects of average temperature on male birth. The shaded area represents the 0.95 confidence interval.

Figure 6: Temperature effect on male birth by number of years lived at place of residence



Notes: The figure above represents the point estimates of the relationship between average temperature during pregnancy and probability of a male birth. This relationship is shown for mothers who have spent more than 10 years in their place of residence at the survey (Panel (a)), and for mothers who have spent less than 10 years (Panel (b)). The coefficient estimates represent the marginal effects of average temperature on male birth. The blue line shows the trend of the relationship between these variables and the shaded area represents the 0.95 confidence interval associated to these points estimates.

Table 1: Descriptive statistics

Variables	N	Mean	St. Dev.
Births			
male	1,985,399	0.508	0.500
alive	1,985,399	0.859	0.348
birth order	1,985,399	3.370	2.276
Average Weather during 9-months pregnancy			
temperature (°C)	1,885,953	23.964	4.360
precipitation (cm)	1,885,953	8.975	9.465
Mother's characteristics			
age at delivery	1,704,866	25.506	6.358
no education	1,917,912	0.438	0.496
single	1,878,060	0.129	0.335
urban	1,985,399	0.263	0.440

Notes: Authors'calculations. The sample period is 1980-2010.

Table 2: Non-linear effects of temperature on male birth

	Dependent variable: male			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Average Temperature Bins (°C)				
< 18	−0.00712**	−0.00526***	−0.00416**	−0.00607***
	(0.00326)	(0.00171)	(0.00174)	(0.00181)
18-22	−0.00380*	−0.00336***	−0.00332***	−0.00634***
	(0.00224)	(0.00109)	(0.00110)	(0.00113)
26-30	0.00407*	0.00331***	0.00267**	0.00566***
	(0.00234)	(0.00125)	(0.00126)	(0.00130)
> 30	0.00369	0.00438*	−0.00048	0.00484*
	(0.00394)	(0.00248)	(0.00248)	(0.00267)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,562,678	1,567,293	1,567,253	1,567,145
R^2	0.09708	0.09717	0.09715	0.09710

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of each temperature bin on male birth by trimester of pregnancy. In all regressions, standard errors are clustered at the DHS cluster level. All regressions control for mother's characteristics comprising age at delivery, marital status, birth interval in month, number of prior children (or child birth order), household wealth index, and educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table 3: Alternative specifications

	Dependent variable:			
	male			
	(1)	(2)	(3)	(4)
Average Temperature Bins (°C)				
< 18	-0.00712^{**}	-0.00512^{**}	-0.00390^{**}	-0.00401^{**}
	(0.00326)	(0.00245)	(0.00175)	(0.00175)
18-22	-0.00380^{*}	-0.00014	-0.00592^{***}	-0.00518^{***}
	(0.00224)	(0.00258)	(0.00111)	(0.00111)
26-30	0.00407^{*}	-0.00126	0.00083	0.00192
	(0.00234)	(0.00249)	(0.00127)	(0.00127)
> 30	0.00369	-0.00274	-0.00277	0.00020
	(0.00394)	(0.00408)	(0.00247)	(0.00247)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y		Y	Y
Mother FE		Y		
Year of Birth FE			Y	
Controls for precipitation				Y
Observations	1,562,678	1,560,472	1,560,472	1,560,472
R^2	0.09708	0.26650	0.09905	0.09709

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equals 1 if the sex at birth is male and 0 otherwise. The table shows temperature effects for the whole pregnancy period — estimated coefficients with standard errors are in brackets. Our standard errors are clustered at region of birth level.

Table 4: Predictions of lower bound of fetal mortality and SRB due to average temperatures

Estimation	Fetal mortality (per 1000 births)	SRB (boys per 100 girls)
Actual	2.1318	102.78
	(0.0023)	(0.1108)
Predicted	3.5195	103.68
	(0.0021)	(0.1566)

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports estimations of fetal mortality and SRB obtained with actual and 2050 predicted distribution of monthly average temperature in our SSA sample. Here, fetal mortality is for males and females pooled together.

Table 5: Heterogeneity in temperature impacts on male birth.

	Dependent variable:			
	male			
	(1)	(2)	(3)	(4)
< 18	-0.00425^{*}	0.01547^{**}	-0.00233	-0.00834^{***}
	(0.00221)	(0.00670)	(0.00296)	(0.00196)
> 30	-0.00737	0.01804	0.00676	0.00433
	(0.00700)	(0.01097)	(0.00496)	(0.00331)
$< 18 \times education$	-0.00346			
	(0.00314)			
$> 30 \times education$	0.00698			
	(0.00727)			
$< 18 \times age$		-0.00060^{***}		
		(0.00019)		
$> 30 \times age$		-0.00058^{*}		
		(0.00032)		
$< 18 \times birth\ order$			-0.00164^{**}	
			(0.00068)	
$> 30 \times birth\ order$			-0.00133	
			(0.00101)	
$< 18 \times urban$				0.01234^{***}
				(0.00364)
$> 30 \times urban$				-0.02650^{***}
				(0.00591)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,823,073	1,823,073	1,823,073	1,823,073
R^2	0.07144	0.07147	0.07060	0.07152

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equal to 1 if the sex at birth is male, and 0 otherwise. The table shows temperature heterogeneous effects for the whole pregnancy period — estimated coefficients with standard errors in the brackets. Heterogeneous characteristics consider mother's education, age at delivery, child's birth order, and place of residence (urban vs. rural). The omitted categories considered are mother having education, and living in rural for variables education, and place of residence (urban or rural), respectively. We run our preferred specification with region and month of birth fixed effects and controls for mother's characteristics. The latter include mother's marital status, ethnicity, and religion.

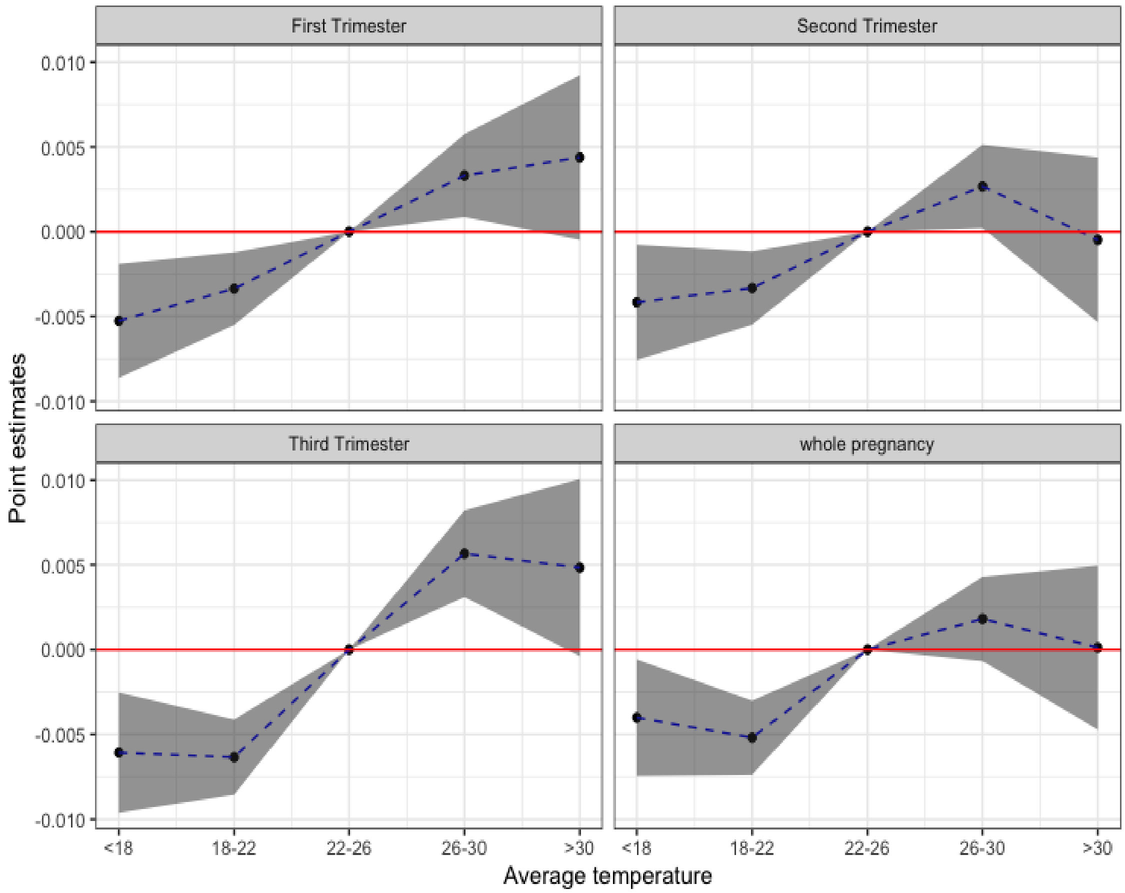
Table 6: Temperature effects on infant mortality

	Dependent variable:		
	infant mortality		
	All	Males	Females
	(1)	(2)	(3)
Average Temperature Bins (°C)			
<18	−0.01399**	−0.01577**	−0.01193**
	(0.00571)	(0.00612)	(0.00567)
18-22	−0.00770**	−0.00747*	−0.00793**
	(0.00390)	(0.00416)	(0.00381)
26-30	0.00642*	0.00604	0.00678
	(0.00387)	(0.00392)	(0.00415)
>30	0.00937*	0.00431	0.01442**
	(0.00555)	(0.00642)	(0.00561)
Region FE	Y	Y	Y
Month of Birth FE	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,878,989	953,998	924,991
R^2	0.02404	0.02560	0.02736

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on infant mortality, that is up to one year after birth. All regressions are clustered at mother level and controls for child birth order. We consider the temperature bins distribution experienced during the whole 9-months pregnancy period. The coefficients estimates are interpreted relative to a reference temperature bin 22-26 °C, with standard errors in brackets.

Appendix

Figure A1: Non-linear effects of temperature shocks on male birth (%)



Notes: The figure above is obtained from DHS data on live births. It represents the point estimates of change in probability of male birth due to temperature bins by trimester of pregnancy. Shaded area represents 0.95 confidence interval.

Table A1: Demographic and Health Surveys (DHS) used in the analysis

Country	DHS Survey Year	Total Births	Sex Ratio
Angola	2016, 2011	35583	1.0292
Benin	2017, 2011, 2001, 1996	77349	1.0542
Burkina Faso	2010, 2003, 1998	88735	1.0381
Burundi	2016, 2010	40167	1.0198
Cameroon	2011, 2004	51330	1.0171
Central Africa Republic	1994	9624	1.0441
Chad	2014	42236	1.0465
Congo Democratic	2007	22007	1.0344
Comores	2012	7516	1.0513
Estwatini	2006	7646	1.0335
Ethiopia	2016, 2011, 2005, 2000	110649	1.0587
Gabon	2012	15336	0.9767
Ghana	2014, 2008, 2003	32053	1.0460
Guinea	2012, 2005, 1999	54386	1.0463
Ivory-Coast	2011, 1998, 1994	38368	1.0283
Kenya	2014, 2008, 2003	79930	1.0356
Lesotho	2014, 2004	15129	1.0250
Liberia	2013, 2007	36250	1.0474
Madagascar	2008, 1997	48807	1.0427
Malawi	2015, 2010, 2004, 2000	142912	1.0137
Mali	2012, 2006, 2001, 1995	121136	1.0398
Mozambique	2015, 2011	26059	1.0003
Namibia	2013, 2006, 2000	31559	1.0018
Niger	1998, 1992	33154	1.0415
Nigeria	2013, 2008, 2003, 1990	189838	1.0382
Rwanda	2014, 2010, 2007, 2005	76816	1.0275
Senegal	2005, 1997, 1992	59009	1.0371
Sierra Leone	2013, 2008	45045	1.0321
South Africa	2016	5421	1.0762
Tanzania	2015, 2010, 1999	49736	1.0010
Togo	2013, 1998	33253	1.0240
Uganda	2016, 2011, 2006, 2000	90954	1.0117
Zambia	2013, 2007	46180	0.9976
Zimbabwe	2015, 2010, 2005, 1999	43177	1.0211
34	85	1807350	1.0305

Notes: This table lists all the sub-Saharan African countries and Demographic and Health Surveys (DHS) used for our analysis. There are 34 countries and 85 surveys in total.

Table A2: Temperature effects on male birth (%) and length of gestational period

	Dependent variable:		
	male		
	Whole Pregnancy (9-months)	8-months	10-months
	(1)	(2)	(3)
Average Temperature Bins (°C)			
< 18	−0.00712**	−0.00649**	−0.00606*
	(0.00326)	(0.00291)	(0.00327)
18-22	−0.00380*	−0.00426**	−0.00412*
	(0.00224)	(0.00204)	(0.00231)
26-30	0.00407*	0.00384*	0.00520**
	(0.00234)	(0.00225)	(0.00226)
> 30	0.00369	0.00268	0.00735*
	(0.00394)	(0.00421)	(0.00393)
Region FE	Y	Y	Y
Month of Birth FE	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,562,678	1,563,425	1,561,949
R^2	0.09708	0.09708	0.09708

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on male birth by length of pregnancy. All regressions are clustered at mother level and contain mother's characteristics such as age, marital status, birth interval in months, number of prior children (or child birth other), educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table A3: Temperature effects on male birth (%) and PSR channel

	Dependent variable:		
	male		
	(1)	(2)	(3)
Before conception (0-3 months)	0.00049	0.00030	0.00023
	(0.00086)	(0.00087)	(0.00082)
First Trimester	−0.00137**	−0.00133**	−0.00063
	(0.00059)	(0.00059)	(0.00050)
Second Trimester	0.00122**	0.00131**	0.00097**
	(0.00059)	(0.00059)	(0.00049)
Third Trimester	−0.00117*	−0.00090	−0.00074
	(0.00067)	(0.00067)	(0.00058)
After Birth (0-3 months)	0.00127	0.00149*	0.00100
	(0.00081)	(0.00082)	(0.00076)
Region FE	Y	Y	N
Month of birth FE	Y	Y	N
Year of birth FE	N	Y	Y
Controls for Mother's Characteristics	Y	Y	Y
Observations	1,409,952	1,409,952	1,409,952
R^2	0.00473	0.01246	0.00112

Notes: *p<0.1; **p<0.05; ***p<0.01. The dependent variable is an indicator equals 1 if the sex at birth is male and 0 otherwise. The regressors of interest involved the monthly temperature at different windows of pregnancy, that is from few months before conception up to 3 months after birth. All regressions are clustered at mother level and contain mother's characteristics such as age at delivery, marital status, birth interval in months, number of prior children (or child birth other), educational attainment, household wealth asset. Our standard errors are clustered at region level.

Table A4: Non-linear effects of average temperature on male birth using number of months in a specific bin as a main regressor

	Dependent variable:			
	male			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Number of months				
< 18	-0.00072	-0.00235^{**}	-0.00161	-0.00078
	(0.00044)	(0.00101)	(0.00106)	(0.00117)
18-22	-0.00079^{*}	-0.00197^{**}	-0.00112	-0.00197^{**}
	(0.00041)	(0.00093)	(0.00081)	(0.00096)
26-30	0.00045	0.00083	0.00089	0.00134^{*}
	(0.00036)	(0.00075)	(0.00073)	(0.00070)
> 30	0.00005	0.00143	0.00011	0.00012
	(0.00053)	(0.00108)	(0.00122)	(0.00097)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y
Observations	1,548,073	1,552,578	1,552,556	1,552,477
R^2	0.09694	0.09700	0.09698	0.09695

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports the non-linear estimate of impact of each temperature bins on male birth by each trimester of pregnancy. These point estimates are obtained with specification 3 in which we replace average temperature by a count variables that is the number of months in a given window of pregnancy where an average temperature fall in a specific bin. All regressions are clustered at DHS cluster level and contain mother's characteristics such as age at delivery, marital status, birth interval in months, number of prior children (or child birth other), wealth asset, educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Table A5: Predictions of lower bound of fetal mortality due to extreme temperatures using different reference bins.

	Fetal mortality (per 1000 births)	
Reference bin	Actual	Predicted
22-26 (Baseline)	2.1318	3.5195
	(0.0023)	(0.0021)
18-22	2.1972	3.7201
	(0.0034)	(0.2106)
26-30	2.4603	3.8103
	(0.0042)	(0.3207)

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports estimations of fetal mortality using different reference temperature bins, from actual and 2050 predicted distribution of monthly average temperature in our SSA sample. Here, fetal mortality is for males and females pooled together.

Table A6: Non-linear effects of temperature on infant mortality

	Dependent variable:			
	infant mortality			
	Whole Pregnancy	First Trimester	Second Trimester	Third Trimester
	(1)	(2)	(3)	(4)
Average Temperature Bins (°C)				
	Panel A. All			
< 18	-0.01399^{**}	-0.01154^{***}	0.00770^{***}	0.00528
	(0.00571)	(0.00438)	(0.00273)	(0.00328)
18-22	-0.00770^{**}	-0.00523^{*}	0.01219^{***}	0.00801
	(0.00390)	(0.00292)	(0.00437)	(0.00538)
26-30	0.00642^{*}	0.00118	0.01293^{**}	0.00337
	(0.00387)	(0.00234)	(0.00525)	(0.00619)
> 30	0.00937^{*}	0.00134	0.01369^{**}	0.00141
	(0.00555)	(0.00366)	(0.00612)	(0.00703)
	Panel B. Males			
< 18	-0.01577^{**}	-0.00983^{**}	0.00771^{***}	0.00331
	(0.00612)	(0.00418)	(0.00245)	(0.00313)
18-22	-0.00747^{*}	-0.00565^{*}	0.01114^{**}	0.00634
	(0.00416)	(0.00301)	(0.00442)	(0.00549)
26-30	0.00604	0.00256	0.01383^{**}	0.00363
	(0.00392)	(0.00262)	(0.00559)	(0.00644)
> 30	0.00431	0.00514	0.01386^{**}	0.00224
	(0.00642)	(0.00388)	(0.00628)	(0.00777)
	Panel C. Females			
< 18	-0.01193^{**}	-0.01300^{***}	0.00759^{**}	0.00723^{*}
	(0.00567)	(0.00496)	(0.00347)	(0.00377)
18-22	-0.00793^{**}	-0.00488	0.01306^{***}	0.00958^{*}
	(0.00381)	(0.00303)	(0.00477)	(0.00557)
26-30	0.00678	-0.00019	0.01184^{**}	0.00295
	(0.00415)	(0.00246)	(0.00549)	(0.00629)
> 30	0.01442^{**}	-0.00269	0.01309^{*}	0.00038
	(0.00561)	(0.00414)	(0.00684)	(0.00709)
Region FE	Y	Y	Y	Y
Month of Birth FE	Y	Y	Y	Y
Controls for Mother's Characteristics	Y	Y	Y	Y

Notes: *p<0.1; **p<0.05; ***p<0.01. The table reports non-linear estimates of the impact of each temperature bin on infant mortality by trimester of pregnancy. We present our results in three panels: the whole sample (panel A); males (panel B); and females (panel C). In all regressions, standard errors are clustered at the DHS cluster level. All regressions control for mother's characteristics comprising age at delivery, marital status, birth interval in month, number of prior children (or child birth order), household wealth index, and educational attainment. In addition, our preferred specification includes region and month of birth fixed effect to account for seasonal variation common to a region.

Notes

N1 How do we recover the fetal death?

In this section, we explain how we recover the magnitude of fetal death. The sex ratio at birth is a product of the primary sex ratio and sex selective intrauterine mortality:

$$SRB = PSR \times SSIM$$

Neither the primary sex ratio nor the sex selective intrauterine mortality are observed directly. We postulate that intrauterine mortality is dependent on temperature during pregnancy and gender of the fetus, such that the probability of fetal mortality (FM) is:

$$FM = \beta \times 1[male] \times 1[extreme]$$

Where *extreme* is a binary variable that is indicative of a temperature extreme experienced by the fetus during pregnancy (i.e., extreme cold or extreme heat), and β is the probability of male fetal mortality as a result of extreme temperature during pregnancy. This simple specification allows for gender-specific differences in fetal response to adverse climatic conditions. With these definitions, we can define the expectation that the gender of a baby is male:

$$\begin{aligned}
E[male] &= PSR \times SSIM \\
&= PSR \times \frac{(1 - \beta \times 1[extreme])}{(PSR(1 - \beta \times 1[extreme]) + (1 - PSR))} \\
&= \frac{(1 - \beta \times 1[extreme])}{(1/PSR - \beta \times 1[extreme])}
\end{aligned}$$

A regression of male on *extreme* will then recover an intercept of PSR and a coefficient on *extreme* of $\frac{\beta(PSR-1)}{1/PSR-\beta}$. For a PSR of 0.5, for example, this reduces to: $\frac{-0.5\beta}{2-\beta}$. For example, if the probability of male fetal mortality during extreme temperature is $\beta = 0.5$, the regression will recover a coefficient of -0.17. In general, as shown in the figure below (Figure N1), the relationship between β and the coefficient recovered in the regression of a male dummy on an extreme temperature dummy is non-linear. Our regression recovers a coefficient of -0.007 from a regression of a male dummy on a cold weather dummy, with controls. Assuming a PSR of 0.5, this suggests that cold weather kills 2.8% of male fetuses (relative to female). Figure N1 below shows how the coefficient depends on β for different values of the primary sex ratio.

Figure N1: Fetal mortality due to extreme temperature