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ABSTRACT

Prenatal Exposure to Heat Waves and Child Health in Sub-saharan Africa*

This paper investigates the consequences of prenatal exposure to hot temperatures on child health in Sub-Saharan Africa (SSA) using a novel indicator of heat waves (the Heat Wave Magnitude Index daily). Leveraging several geo-referenced waves of the Demographic and Health Surveys merged with gridded data on the presence of heat waves and their magnitude since the 1980s, we investigate the effects of inutero exposure to heat waves on several birth and early childhood health outcomes (birth weight, low birth weight, weight-for-age and height-for-age z-scores, undernutrition, severe undernutrition, stunting, severe stunting, anemia). Our analysis demonstrates very robust negative effects on long-term child health, namely the probability that the child is severely stunted. Effects are larger for in-utero shocks experienced in the second and third trimesters of pregnancy and for heat waves of higher intensity. We further show that, at least in the SSA context, adaptation mechanisms such as access to improved water and sanitation, electricity, and improved housing do not appear to significantly attenuate the negative effects of heat waves.

JEL Classification: heat waves, child health, Sub-Saharan Africa
Keywords: I14, I15, Q54, J13

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1 Introduction

A growing body of research has analyzed the effects of various fetal shocks on children's outcomes, both at birth and later in life. This paper builds on Barker's fetal origins hypothesis (Barker, 1990, 1995), which posits that access to nutrition in early life has long-run effects on individual health and well-being. In other words, some chronic health conditions can be tracked to the course of fetal development. Early life shocks such as famines, epidemics, and recessions affect fetal programming and consequently lead to lower cognitive attainment, morbidities, and lower life expectancy.[1]

Among the several shocks that children may experience in utero, of particular importance are weather-related shocks, which have become increasingly topical in recent times. Indeed, in the coming decades, with global warming and increasing global mean temperatures, heat waves (periods of excessively hot weather) will become longer, hotter, and more frequent than in the present climate (Russo et al., 2014).[2]

Africa is one of the continents most vulnerable to climate extremes due to its high exposure and low adaptive capacity (Barros et al., 2014). The occurrence of extreme heat waves is also expected to be more likely in Africa than in other continents (Russo et al., 2014, 2016), and it is liable to bear the brunt of the effects of extreme weather shocks, despite having contributed little to their cause. The last 50 to 100 years have seen near-surface temperatures increase by 0.5°C or more over most parts of Africa (Hulme et al., 2001; Stern et al., 2011; Nicholson et al., 2013). Hence, in the upcoming decades, the occurrence of heat waves could have a strong impact on human mortality and crop production in Africa (Russo et al., 2016).

We focus on potential *short- to medium-term effects* on child health (e.g., at birth or in the first 5 years of life) of heat waves experienced while *in utero* using Demographic and Health Surveys (DHS) data. Understanding how weather-related shocks impair child health is crucial, especially to develop the strategies needed to reduce the potential long-term consequences of such shocks on human health. However, evidence for the African continent is still sparse. The few extant studies either provide evidence on single countries (e.g., Mulmi et al., 2016), on one or a few (often short-run) proxies of child health such as birth weight (e.g., Grace et al., 2015; Davenport et al., 2020), or on relatively rare and extreme events such as child death (e.g., Kudamatsu et al., 2016; Wilde et al., 2017).

In this paper, we seek to improve our knowledge of the effects of extreme temperatures on child health. To this end, we focus on Sub-Saharan Africa (SSA), one of the regions most at risk of experiencing the negative impacts of rising temperatures, both because of the incidence of the phenomenon and the lack of coping mechanisms. We employ a new indicator of heat haves, the Heat Wave Magnitude Index daily (HWMId hereafter;

[1] Events such as famine (Kannisto et al., 1997; Lindeboom et al., 2010; Portrait et al., 2011; Xu et al., 2016), Ramadan fasting (Almond and Mazumder, 2011; Van Ewijk, 2011; Majid, 2015), epidemics (Almond, 2006; Banerjee et al., 2010; Neelsen and Stratmann, 2012), government interventions (Field et al., 2009; Lucas, 2010), and extreme weather shocks (Maccini and Yang, 2009; Skoufias and Vinha, 2012; Grace et al., 2015; Rocha and Soares, 2015; Wilde et al., 2017; Shah and Steinberg, 2017) experienced in utero have been found to affect children's outcomes. Economists have investigated how prenatal shocks and other conditions affect not only health later on in life but also a range of other outcomes including test scores, educational attainment, income, and socioeconomic status in general (Almond and Currie, 2011a,b).

[2] A more precise definition of heat waves is given in Section 2.

see Russo et al., 2014, 2015; Zampieri et al., 2016), which combines both the length and intensity of heat episodes in a single indicator and is able to capture events that are perceived as heat waves by a broader public and are well documented in the news (see Section 2.1 for the details). Compared to the extant literature, we study the effect of prenatal exposure to heat shocks on several child health outcomes both at birth (including birth weight and low birth weight) and after birth (such as height-for-age, weight-for-age, stunting, being underweight, anemia, and mortality). A heterogeneity analysis is carried out to assess which groups (i.e., socioeconomic groups and gender) are more exposed to the health damages of heat waves. Finally, we report extensive evidence on the availability and effectiveness of possible adaptive strategies in the SSA context (e.g., housing type, water and sanitation, electricity and refrigeration, urban residence, and prenatal healthcare).

In order to address potential omitted variable biases owing to unobservable characteristics that may make some regions/periods of the year more likely to be hit by heat waves or provide poorer conditions for healthy child development, we leverage presumably exogenous variation in a child's exposure to extreme temperatures while in utero by exploiting *within district-month of birth* differences in the incidence of heat waves across years of birth. In so doing, we compare two children who were born in the same district (for instance, Gushiegu district in the northern region of Ghana) in the same month (say, November) but in two different years: one in which that district was affected by heat waves in the 9 months before the mother gave birth and one in which that same district was not affected by such shocks. The strategy of including district-month of birth fixed effects has been already followed in the literature (e.g., Wilde et al., 2017; Kumar et al., 2016) because it allows controlling for time-invariant district-month of birth unobservable variables. For instance, women who decide to conceive children in given months of the year (e.g., winter months) may systematically differ from those who conceive in other months (e.g., summer) in terms of characteristics that correlate with child health, and this selection may be district-specific (e.g., may be stronger in hotter compared to colder districts). Hence, district-month of birth fixed effects allow for attenuating potential selective fertility issues.

In addition to using a novel indicator of heat waves, our paper differs from recent work focusing on SSA countries (using the DHS) in a number of ways. Grace et al. (2015) and Davenport et al. (2020) only investigate birth weight outcomes and use different empirical specifications based on a less comprehensive set of fixed effects. We show in Section 4 that some results are sensitive to the fixed effects included in the models. Unlike Wilde et al. (2017), we investigate the effect of all prenatal heat shocks—not specifically at conception—on child health, while the former mainly focus on adult health (e.g., disabilities) and non-health (e.g., educational) outcomes. In comparison to Baker and Anttila-Hughes (2020), who focus on heat shocks in the month of the survey, the year leading up to the survey, and a childs lifetime, we study prenatal shocks.[3]

We find robust evidence that exposure of a child to heat waves in utero increases the probability that s/he is severely stunted (height-for-age z-score lower than 3) by 1.4 pp

[3] Moreover, when considering long time horizons for exposure to climatic events, it is much more difficult to have precise measures of exposure—owing to individual mobility (as information on where the child lived in each year is generally not available)—and to claim exogeneity, as mobility may be partly due to environmental factors (Piguet et al., 2011).

(8%). Effects on stunting are larger in the first and second trimesters of gestation, while a negative effect on birth weight emerges for shocks experienced in the second and third trimesters (−23 g.). Although large effects on long-term child health are produced by even moderate intensity heat waves, effects are larger for very high intensity heat waves (HWMId larger than 9).

Our analysis of the potential mechanisms does not point to food scarcity as the main explanation for the negative effects of heat waves, albeit this finding may be partly due to data limitations. As for the adaptation strategies potentially available in the SSA context, we show the ineffectiveness of factors such as better access to improved water and sanitation, improved housing, or access to electricity, while our findings demonstrate that improving access to prenatal care may be an effective way of reducing the harmful effects of in-utero exposure to heat waves.

The rest of the paper is organized as follows. Section 2 describes the data sources and the main features of the dependent and independent variables used in the empirical analysis. Section 3 explains the empirical strategy. The main results are presented in Section 4, while some selectivity and measurement error issues are discussed in Section 5. The relevance of potential adaptation strategies to cope with heat waves in the SSA context is discussed in Section 6. Section 7 draws conclusions.

2 Data

We pool comprehensive information on mothers and their children and geo-referenced data on weather variables to construct a dataset for 20 Sub-Saharan African countries over the period of 1990 through to 2016. Table A in the Appendix provides detailed information on the countries and the survey waves used in the empirical analysis. The types and sources of data used are explained in the following sections.

2.1 Heat waves

2.1.1 Calculation of the Heat Wave Magnitude Index daily (HWMId)

Daily maximum temperature and precipitation data from the ERA-Interim (ERA-I) reanalysis from the European Centre for Medium-Range Weather Forecasts (Dee et al., 2011) are used to gather data on heat waves in the past and present climate in Africa. The dataset has a 6-hourly time resolution and is available from January 1979 to January 2016. The ERA-I is based on a T255 resolution (0.7^o, 79 km).[4] The magnitude of heat waves is estimated on a seasonal scale by means of the Heat Wave Magnitude Index daily (HWMId), following Russo et al. (2015) and Russo et al. (2016).

[4] The same source of data is used to compute measures of precipitation and drought. Although precipitation and drought are not the main focus of this paper, we include them as control variables in some regression models to check the sensitivity of our results. More specifically, we use the Standardized Precipitation Index (McKee et al., 1993).

In order not to split heat waves that start in a 3-month block and end in the consecutive 4th month not included in the block, the HWMId is calculated for 12 moving blocks of 3 months: January–February–March, February–March–April, ..., December–January–February (see Russo et al., 2016). Following Russo et al. (2016), a heat wave is defined as *a period of at least three consecutive days with a maximum temperature (T_{max}) above the daily threshold for the reference period 1981–2010*. The threshold is defined as the 90th percentile of daily maxima, centered on a 31-day window. The magnitude of a heat wave is calculated by summing the magnitude of each hot day comprising a heat wave and the daily magnitude (M_d) at each grid point, as described in Russo et al. (2015):[5]

$$M_d(T_d) = \begin{cases} \frac{T_d - T_{30y25p}}{T_{30y75p} - T_{30y25p}} & \text{if } T_d > T_{30y25p}, \\ 0 & \text{if } T_d \leq T_{30y25p}, \end{cases} \tag{1}$$

where T_d is the daily maximum temperature on day d of the heat wave. T_{30y25p} and T_{30y75p} are, respectively, the 25th and 75th percentiles (i.e., first and third quartiles) of the time series composed of 30 annual T_{max} within the reference period 1981–2010. The slope of $M_d(T_d)$ depends on T_{30y75p} and T_{30y25p}, which in turn are location-specific.

The units in which the magnitude of heat waves is expressed have an immediate interpretation. The denominator of the M_d function is the interquartile range (IQR) of the 30 yearly T_{max} within the reference period (1981–2010) and represents a non-parametric measure of the variability of the time series composed of the annual T_{max} in the same period. Thus, temperature anomalies are defined according to the temperature variability in each location. If a day of a heat wave has a temperature value T_d equal to T_{30y75p}, its magnitude will be equal to one, if T_d exceeds the 25th percentile of T_{max} by twice the IQR, the heat wave magnitude is two, and so on.

The HWMId is preferred to other indexes because it enables comparing heat waves occurring in different regions and in different years. In particular, the HWMId has the desirable feature of merging several climate-related measurements of heat events (i.e., duration and intensity) into a single number. It has the advantage of defining the severity of the heat events on the basis of global thresholds, and thus no longer depends on the region (Russo et al., 2014, 2015; Zampieri et al., 2016). Last but not least, the HWMId has been validated with historical data. Russo et al. (2015), for instance, show that in contrast to some previous indexes HWMId captures events that are perceived as heat waves by a broader public and are well documented in the news.

2.1.2 Heat waves in Sub-Saharan Africa

In this section, we present the distribution of heat waves in SSA over the period of 1979 to 2016. We first show the distribution of heat waves across districts according to their level of intensity. There is marked variation in climatic conditions in SSA over the period of 1979 to 2016. Figure 1 presents the map of the distribution of heat waves for the period under analysis and indicates significant exposure of many districts to heat waves. As the figure shows, the great majority of districts were exposed to heat shocks during the period of analysis; therefore, variation in most of the districts can be leveraged to

[5] The HWMId calculation has been carried out using the HWMId function recently included in the R package called "extRemes" (Gilleland and Katz, 2016).

identify the causal effects of heat waves.

Figure 2 shows the proportion of districts exposed to extreme heat waves (HWMId is above 3) and no heat waves (HWMId is 0) between 1979 and 2016. The historical pattern shows that heat waves occur frequently and quite unpredictably. Generally, significant proportions of districts experience heat waves and extreme heat waves ($HWMId > 3$), particularly after 1996. This suggests that there has been an increase in the probability of observing heat waves across many districts in SSA, which corroborates the information on the map in Figure 1.

[Figure 1 around here]

[Figure 2 around here]

2.1.3 In-utero exposure to heat waves

To define a measure of a child's exposure to heat waves, we carry out the following steps. First, we follow Russo et al. (2014) to classify heat waves according to the HWMId. Geographical areas with HWMId values of zero are considered "not exposed" to heat waves. Conversely, areas with positive values are considered "exposed" to heat waves, albeit to different degrees. Thus, we first create a binary indicator for whether or not a district-month-year was hit by a heat wave, that is, whether or not the corresponding HWMId is positive or zero. Second, we create additional binary indicators reflecting the severity of exposure measured by the HWMId, which are defined following Russo et al. (2016) as: $(0, 3]$, $(3, 6]$, $(6, 9]$, and $(9+)$. Having defined these variables, we then simply construct indicator variables for heat shocks overlapping with the period of pregnancy. Namely, we create an aggregate dichotomous indicator for whether a child was exposed to a heat shock in utero and dichotomous indicators for the intensity of the shocks.[6]

2.2 Demographic and Health Surveys (DHS)

Our empirical analysis is based on the DHS, which gather detailed and representative household-level data on the health and demographic characteristics of populations living in developing countries across the world. The DHS data are also spatially referenced and provide latitude and longitude values for the *current residence* of their sampled clusters.[7] These clusters are randomly spatially displaced up to 10 km (5 km) from their actual urban (rural) locations. This is intended to preserve the anonymity of the respondents. Additionally, the DHS collect detailed micro-level information about maternal characteristics and provide retrospective information about the health of infants and children.

Initially, we used every DHS between 1990 and 2016 for which the global positioning system (GPS) datasets are available, for a total of 84 surveys across 31 countries. The

[6] As for precipitation, which is controlled for in some regression model specifications, following the literature positive rainfall shocks are defined as a Standard Precipitation Index (SPI) between +1 and +2 standard deviations and drought is defined as less than −1 standard deviations (see McKee et al., 1993, for more details). Also in this case, a child is exposed if the mother experiences these shocks during gestation.

[7] A cluster in the DHS is, by definition, a geographic location that represents the centroid of the area where the respondent resides.

GPS datasets provide information on the geographical coordinates of each DHS cluster in the sample. Using DHS unique cluster identifiers, we matched the surveys to their respective shape files. We further used the geo-referenced DHS and matched them to the shape files of their second administrative regions (hereafter referred to as *districts*). Using QGIS geospatial software and the district shape files, we overlaid the gridded SPI and HWMId datasets onto the districts in the DHS to generate a monthly panel of weather variables corresponding to each district. Since the SPI and HWMId data come in a raster form, we calculated the mean and the maximum values of the pixels of the raster layers that were within each polygon, which generates output columns in the vector layer. We dropped from the sample observations for which no HWMId data were available. We further dropped children born from multiple births (duplets, triplets, etc.)—since twinning is commonly related with a lower weight at birth (Kramer, 1987)—and children whose anthropometric measures are considered biologically implausible (Mei and Grummer-Strawn, 2007).[8] Finally, we excluded all children whose birth weights were observed to be above 6,500 g or below 500 g, as these are beyond the normal range according to the medical literature (Doubilet et al., 1997). It must be noted that exposure to heat waves during pregnancy based on current residence may suffer from measurement error. Unfortunately, the full residential history is not collected by the DHS and geo-referencing only applies to the current residence. However, the DHS provide information on the number of years a household lived in the current location, so we follow previous studies and restrict our analysis to mothers who spent their gestational period where they currently reside (cf. Grace et al., 2015; Davenport et al., 2020). The final sample includes 53 surveys covering the 1990–2015 period for 20 Sub-Saharan African countries (see Table A1 in the Appendix for the complete list).[9]

2.2.1 Anthropometric measures

During the DHS interviews, qualified and trained nurses collect objective measures of *weight* and *height*, and data collection for all children in the sample is comparable across all surveys. We construct two anthropometric z-scores, namely weight-for-age z-score (WAZ) and height-for-age z-score (HAZ), using the 2006 WHO child growth standards for all children aged 0–5 years of age by sex.[10] Additionally, we construct the binary variables *stunting* and *severe stunting* based on WHO definitions: equal to one if the child's HAZ falls below -2 and -3 standard deviations, respectively, from the median height-for-age. Similarly, we construct two additional binary variables *underweight* and *severe underweight* equal to one if the child's WAZ falls below -2 (-3) standard deviations from the median weight-for-age (World Health Organisation, 2015).[11] The use of these

[8] Based on the WHO's new 2006 cut-off value, the following measures are considered biologically implausible: if a child's height-for-age z-score is below -6 or above $+6$, weight-for-age z-score is below -6 or above $+5$, weight-for-height z-score is below -5 or above $+5$, or body-mass-index z-score is below -5 or above $+5$.

[9] For some countries, there was no information on the HWMId for the entire period, whereas it was missing for some years for other countries. For instance, Senegal is excluded from the sample since it had no information on the HWMId for every year considered. For other countries, such as Ghana, some observations with missing HWMIds were dropped from some survey years.

[10] The Stata code `zcore06` (De Onis, 2006) was used to carry out the computation.

[11] Standard equipment and methods are used to measure children's weight and height. For example, children younger than 24 months are measured lying down, while standing height is measured for children

measures is consistent with our goal of assessing the impact of early exposure to heat waves as they generally capture inadequate nutritional intake during the early stages of child development. These developments usually occur before age two and have long-lasting effects once they are established.[12]

2.2.2 Additional health outcomes

We complement the anthropometric measures with other health-related measures. Recent waves of the DHS gather blood samples from children during data collection. Hemoglobin levels adjusted for cluster altitude are used to create a categorical variable for anemia level (not anemic, mild, moderate, and severe) according to WHO standards. Based on this classification, we construct a binary variable equal to one if a child is reported to have at least mild anemia and zero if he/she is not anemic. Anemia is usually a measure of poor nutrition (i.e., iron deficiency) and poor health (World Health Organisation, 2008). We also employ information on birth weight and the incidence of low birth weight among newborns as an additional measure of child health (at birth). Again, we use the WHO definition of low birth weight (i.e., birth weight less than 2,500 g.). Finally, we also investigate child mortality.

2.2.3 Descriptive statistics

Columns (1)–(3) of Table 1 present the sample descriptive statistics for the variables used in the empirical analysis. The mean WAZ is −0.96, with approximately 20% and 7% of children undernourished or severely undernourished, respectively. Thus, in our SSA child sample approximately one fifth suffer from some form of malnutrition. Similarly, the HAZ average is around –1.48, with approximately 39% and 18% of children stunted or severely stunted, respectively. The average birth weight of a child is 3.2 kg. The data also show that about 60% of children suffer from at least mild anemia.

Half of the children in the sample are boys, and the average age is about 29 months. Most mothers have lower than primary education (77%). Only 26% have an urban residence. On average, a woman in the sample is 29 years old and the mothers' average age at birth for the children whose outcomes are analyzed is 27 years. About 47% of children experienced heat shocks in utero over the period of 1979 to 2016, but with varying intensities. For instance, only 3% were hit by heat waves above the magnitude of 9, while about 30% were exposed to magnitudes in the range of 0 to 3.

Columns (4)–(5) report the descriptive statistics for the whole sample of children with valid anthropometric measures, including movers, i.e., individuals who changed their area of residence since pregnancy. The comparison offers some hints regarding the sample selection bias that focusing on "stayers" may generate. Means are generally very close.

[Table 1 around here]

aged 24 months and older.

[12] Indeed, for most children it is quite unlikely that they will regain the height lost during this period or achieve a normal body weight.

3 Empirical strategy

Our empirical approach exploits variation in a child's exposure to heat waves within a given district-month cell across years while in utero. We estimate the effect of prenatal exposure to heat shocks on early child health using the following model:[13]

$$h_{i,c,d,m,y,t} = \theta_{c,y} + \gamma_{d,m} + \beta T_{d,m,y} + \psi \mathbf{X}_{i,c,d,m,y,t} + \varepsilon_{i,c,d,m,y,t}, \tag{2}$$

where $h_{i,c,d,m,y,t}$ is the health outcome measured in survey t for a child born in country c in district d in month m and in year y; $\theta_{c,y}$ is a country-year of birth fixed effect and $\gamma_{d,m}$ is a district-month of birth fixed effect. Our regressor of interest is $T_{d,m,y}$, which is an aggregate indicator for exposure to heat shocks for the entire period of gestation. Additionally, we include a vector of child, maternal, and household characteristics $\mathbf{X}_i$, reported in the regression table footnotes. $\varepsilon_{i,c,d,m,y,t}$ is an idiosyncratic error term.

Our strategy compares the health outcomes of children prenatally exposed to unusually hot temperatures against the outcomes of children who are not exposed to such heat shocks. The key independent variable is "exposure to heat wave" during gestation. Our identifying assumption is that the occurrence of a heat wave shock is a quasi-random event within a district over time, and thus the assignment of exposure to a heat wave in utero is "as good as random". To address potential omitted-variable bias related to the fact that children born in certain countries, years, and months may be more likely to be exposed to heat waves, but also to unobserved factors affecting their future health outcomes, we include in the model country-year and district-month fixed effects. They control, *inter alia*, for business-cycle effects and month- (or season-) of-birth effects, which have been found to affect children's outcomes (see, for instance, Dehejia and Lleras-Muney, 2004; Buckles and Hungerman, 2013; Bozzoli and Quintana-Domeque, 2014). To put it simply, the kind of between-individual variation we leverage is that existing between children born in the same district and month but in two different years, one in which a heat wave took place in the nine months preceding the month of childbirth and another in which there was no such event. We cluster standard errors at the district level since exposure is invariant within each district-month in each single year and there is a possible correlation of errors within districts of the same country over time (Pepper, 2002).

Our analysis is further developed by disaggregating exposure according to the trimester of pregnancy, in order to identify in which gestational periods the effects are concentrated. Thus, we estimate the following variant of equation (2) as follows:

$$h_{i,c,d,m,y,t} = \theta_{c,y} + \gamma_{d,m} + \sum_{j=1}^{3} \beta_j T^{j}_{d,m,y} + \psi \mathbf{X}_{i,c,d,m,y,t} + \varepsilon_{i,c,d,m,y,t}, \tag{3}$$

where $T^{j}_{d,m,y}$ is the indicator for exposure to heat shock for trimester j.

Identifying the exact trimester of pregnancy would be ideal if we could count forward from the day of conception. Regrettably, information on pre-term births and the last day of menstruation of mothers is lacking in the DHS, which prevents the exact calculation of the full length of pregnancy and the precise identification of trimesters of gestation.

[13] See Wilde et al. (2017) or Molina and Saldarriaga (2017) for a similar specification.

Thus, assuming all pregnancies last 9 months, we calculate the trimester of pregnancy by counting backward from the child's month of birth.[14]

Equation (2) is also estimated using binned dichotomous variables for heat waves of different intensity following the categorization in Russo et al. (2016).[15]

4 Main results

The effect of prenatal heat shocks on birth weight in SSA has been investigated in the past (Grace et al., 2015; Davenport et al., 2020).[16] In addition to considering a larger set of child health outcomes, our paper differs from these previous contributions mainly in the indicators employed to measure heat shocks, which are generally defined in absolute (usually as temperatures above 100°F or 105°F) and not in relative terms (i.e., in relation to the normal temperatures in a given location) like in the HWMId,[17] and in the set of fixed effects included in the estimation. Hence, to ease comparability with the extant literature, before estimating the more demanding specification of equation (2), we report the results of using less comprehensive sets of fixed effects.

[Table 2 around here]

Panel (a) of Table 2 shows the results of the models including separate country and month-of-birth fixed effects (cf. Grace et al., 2015). The results show a counterintuitive positive — but very small — effect on WAZ and positive effects on being underweight and severely underweight, which are all statistically nonsignificant, however. The results on HAZ are consistent with expectations, with a (nonsignificant) negative effect on HAZ and positive effects on stunting and severe stunting that are quite sizeable, amounting to about 1.2 and 1.7 percentage point (pp hereafter) increases in the dependent variables associated with an in-utero heat shock. However, only the latter is precisely estimated and statistically significant at the 1% level. It corresponds to a 10% increase in the probability of severe stunting over the baseline, i.e., for the population of children not affected by in-utero shocks (of whom about 16.5% are severely stunted, as reported in the last row of the table). The effects on birth weight and low birth weight are consistent with heat waves negatively impacting outcomes at pregnancy and are qualitatively in line with Grace et al. (2015) but are small and far from being statistically significant.[18] As noted

[14] This is likely to cause problems especially for shocks experienced early during the pregnancy, since in case of pre-term births first-trimester shocks may in reality be pre-conception shocks.

[15] We do not do the same for equation (3), i.e., we do not allow heat waves of different intensities to have differential effects by trimester of gestation, since the estimates suffer from a problem of small cell sizes—especially for high intensity categories, which are quite rare.

[16] Evidence of negative effects of high temperatures on birth weight has been reported for several countries, including the US (Deschênes et al., 2009), Andean countries (Andalón et al., 2016; Molina and Saldarriaga, 2017), and China (Chen et al., 2020), among others.

[17] In a recent paper, Masiero et al. (2021) compare absolute and relative temperature measures and conclude that the former are more effective in capturing the adverse effects of shocks on health outcomes.

[18] Our sample does not include exactly the same period and countries, however. Since in Grace et al. (2015) standard errors are not clustered, we re-estimated the model without clustering and the coefficients on heat waves remained nonsignificant at conventional levels for birth weight and low birth weight. Our results may not be directly comparable to theirs because they report heat wave exposure divided by trimester of gestation. We report a similar analysis below in this section.

in the data section, a problem with birth weight outcomes in the DHS is that they are often based on memory recalls and are likely to be affected by measurement errors, which bias the estimates towards zero. A problem with this specification is that country-year fixed effects are not included and the effect of heat shocks may be confounded with that of any time-variant unobservable varying at the country level.

This issue is addressed in the specification used by Davenport et al. (2020) that includes country-birth month and country-birth year fixed effects and is reported in panel (b) of Table 2. Compared to the results in panel (a), the inclusion of country-year fixed effects particularly changes the estimates on weight-related outcomes. Indeed, now large and statistically significant negative effects are estimated for WAZ and positive effects on underweight and severe underweight, of −0.05 standard deviations and about 2.4 and 1 pp, respectively. The estimated effects on height-related outcomes are always statistically significant and larger than in panel (a). In particular, in-utero heave waves reduce HAZ by 0.07 standard deviations and raise the likelihood of stunting and severe stunting by about 2 and 2.3 pp, respectively. The inclusion of country-year fixed effects is key to control for country-specific factors that may be simultaneous with temperature shocks and negatively impact childrens outcomes, and we see that they indeed make a difference for weight outcomes. In this specification, identification stems from variation in heat waves across districts and months of births within the same country-year cell. Interestingly, effects on birth weight and low birth weight remain statistically nonsignificant.[19]

Panel (c) of Table 2 reports the estimates of equation (2), which controls for district-month of birth and country-year of birth fixed effects. Compared to Davenport et al. (2020), potential birth-month effects on child health are allowed to be *district specific*. This specification, which has already been followed in previous work (Kumar et al., 2016; Wilde et al., 2017; Molina and Saldarriaga, 2017, cf.), allows us to better control for all kinds of selectivity that are district- and birth-month-specific. As described in Section 3, this enables us to leverage variation within district-birth month cells over time. For instance, it may happen that at the sub-national level, districts that are more exposed to heat waves also have worse institutions or economic conditions (i.e., long-term effects of climate change), which cannot be captured by country-year fixed effects. It is worth noting that in adopting this specification, we abstract from the long-run effects of climate change, i.e., the increased frequency of heat waves (at the district or country level), but compare children that were exposed vs. not exposed to in-utero heat waves because of year-to-year variation in weather conditions in the same month and district of birth. Using this model specification in panel (c), only long-term nutrition outcomes turn out to be negatively affected by heat waves. Only the effect on the probability of severe stunting is statistically significant and negative, −1.4 pp, corresponding to a 8% increase on the baseline.[20]

All in all, Table 2 conveys a mixed picture of the negative effects of heat shocks. On

[19] Davenport et al. (2020) report negative effects of high temperatures on "healthy birth weight' (vs. low birth weight or abortion/miscarriage/stillbirth) but much less clear evidence on low birth weight (vs. healthy birth weight or abortion/miscarriage/stillbirth). Our results may not be directly comparable as our analysis is limited to children alive at the time of the DHS. The effect of heat waves on child mortality are investigated in Appendix B.

[20] In Table A2 in Appendix A, we check whether our preferred estimates are robust to controlling for precipitation.

the one hand, long-term child health outcomes—namely severe stunting—appear to be negatively impacted by heat waves, an effect that is very robustly estimated irrespective of the type of fixed effects included. On the other hand, we find no evidence of harmful effects of heat waves on weight-based outcomes either at birth or post-birth when using a model specification that allows controlling for children's within-country unobserved heterogeneity by month of birth.

There are several reasons why we may fail to estimate significant effects of heat waves on child health, even when these effects exist. A possibility is that the specification of equation (2) is too demanding on the data. Namely, there might be too little variation left in the in-utero exposure to heat waves indicator after controlling for district-month of birth and country-year fixed effects. To check that this is not the case, we regressed the heat wave indicator on the fixed effects and obtained an R^2 of 0.39, which demonstrates that there is sufficient residual variation.[21]

For some variables, namely birth weight and low birth weight, the results may be affected by measurement errors in the dependent variable, which lower the precision of the estimates. In about 45% of cases, children's birth weights in the DHS do not come from administrative records but from mothers' recall. When the estimation is limited to the former, the estimated coefficients on birth weight and low birth weight are larger and of the expected sign (-13 and 0.3, respectively) but still statistically nonsignificant. The sample size approximately halves, however, and the source of the birth weight in the DHS may be non-random, e.g., with respect to exposure to heat waves. Thus, it is hard to assess whether with all of the data coming from administrative records the estimated effects would be different.[22] It is a fact, though, that studies using administrative birth records for other countries generally report negative effects of heat shocks on child birth weight (Deschênes et al., 2009; Chen et al., 2020).

Another possibility is that the exposure to heat waves indicator, mainly measuring the extensive margin, may not be well-suited to capturing the health effects of heat waves. Thus, we considered alternative ways of measuring exposure to heat shocks, in particular, splitting the exposure indicator by trimester of gestation and using bin dummies for the maximum intensity of heat waves experienced during pregnancy.

[Table 3 around here]

Panel (a) of Table 3 shows the results when the exposure indicator is measured by trimester of gestation, i.e., the model in equation (3). The estimated coefficients are often quite small for all trimesters, even for severe stunting (0.5 pp). However, exposure to heat waves in the third trimester turns out to reduce weight at birth by 12 g (4%) and to increase the probability of having a low birth weight by 0.6 pp (7%).

Heat waves are "indivisible", i.e., the HWMId that is used to define heat waves takes into account both the intensity and duration of temperature anomalies. Therefore, heat waves spanning several trimesters (e.g., the end of a trimester and the beginning of the following trimester) may generate a strong correlation between exposure indicators in the different trimesters and multicollinearity problems (as each exposure indicator captures the effect over and above exposure in the other trimesters). To avoid this issue,

[21] The R^2 is 0.39 when the control variables are included.

[22] Full results are available upon request.

we built mutually exclusive indicators of exposure defined on the basis of the different combinations of trimesters in which a child was exposed to heat waves (e.g., 1-0-0 if she was exposed in the first trimester, 1-1-0 if she was exposed in the first and the second trimester, and so on). The results are reported in panel (b) of Table 3. Interestingly, we are now able to replicate the results of Table 2 on severe stunting. In particular, exposure to heat waves is particularly harmful for height in the first and second trimesters of gestation. These results are consistent with the findings of Rabassa et al. (2014) for Nigeria.[23] In contrast, the worst birth weight outcomes are observed for children exposed in all trimesters (-21 g) or in the second and third trimesters (-23 g), although this is statistically significant (at 10%) only in the latter case.[24]

[Table 4 around here]

In Table 2, exposure is only measured in its extensive margin, but its intensity may matter too. Therefore, in Table 4 we use bin dummy indicators for the highest intensity heat wave experienced during pregnancy (computed according to the maximum HWMId). The results are consistent overall with those in Table 2. All heat wave categories are associated with a higher probability of severe stunting, with some evidence of the highest intensity category (HWMId>9) being more harmful (1.9 pp increase in severe stunting compared to 1.3–1.4 pp increases for the other categories).

All in all, the analysis in this section leads us to conclude that the most robust evidence of the adverse effects of heat waves on health concerns child height.

The average estimated effects presented in this section may hide substantial heterogeneity by either maternal or child characteristics. Thus, in Table A3 in the Appendix, we investigate whether the effect of heat waves changes with the level of maternal education (panel (a)) or child gender (panel (b)). Interestingly, the interaction with high maternal education (i.e., secondary schooling or higher) has a negative sign. A mother with high education halves the negative effect of heat waves on childrens severe stunting compared to a low-educated mother, and the effect is no longer statistically significant. This may be explained by better-educated mothers being able to buy goods or services that limit the harmful effects of heat shocks (e.g., access to food, electricity, improved water, and sanitation, etc.) or by maternal education directly providing the health-related knowledge that helps mothers protect their children from extreme heat. This aspect is investigated in Section 6 on adaptation strategies. As for the interplay between heat waves and child gender, panel (b) shows that sons and daughters are similarly negatively affected by heat.

5 Selectivity issues

There are various reasons why our identification strategy may lead to upper- or lower-bound estimates of the effect of interest. They are generally related to individual selection

[23] Skoufias and Vinha (2012) do not find generalized effects of positive temperature shocks on child height in rural Mexico, although they do find negative effects on boys, children aged 12–23 months, and those born to less educated mothers in some regions.

[24] Grace et al. (2015) find larger negative effects on birth weight for heat shocks in the first and second trimesters in a pooled analysis (model 4, Table 3 in their article) and very similar effects across trimesters for Agropastoralists, Pastoralists, Urban, Fishers and Irrigated countries (Table 3a in their article).

due to in-utero or post-birth mortality or differential fertility behavior.

First, in order for a child to be observed in our estimation sample, s/he must survive a heat wave. However, a child may die during pregnancy or after pregnancy, and the probability of death may be affected by in-utero exposure to heat waves (i.e., non-random selection). For this reason, in Appendix B.1 we discuss fetal selection and post-birth child mortality, which can also be considered two extreme health outcomes.

Second, parents who decide to conceive and carry a pregnancy to term during a heat wave may be a non-random sample of the population according to children's potential health outcomes. For instance, parents may be negatively selected (e.g., lower-educated), causing a spurious correlation between heat wave exposure and children's health outcomes. Fertility behavior and selection into parenthood are examined in Appendix B.3.

In general, the analysis in Appendix B does not point to any strong form of selection and suggests that our estimates are unlikely to suffer from important biases.[25]

6 Mechanisms and adaptation strategies

In this section, we investigate what adaptation strategies are available to households in SSA to limit the negative effects of heat waves on child health. This analysis also indirectly hints at the mechanisms that may be behind the health-damaging effect of heat waves. Indeed, although heat waves are likely to directly impact individual health through heat stress, some effects may be mediated by 'macro' factors such as food availability or the spread of infectious diseases.

6.1 Food insecurity: urban residence, number of older siblings

Food scarcity is an important determinant of both children's short- and long-term health outcomes (Miller, 2017), and heat waves may negatively affect food availability (Zampieri et al., 2017). Mulmi et al. (2016), for instance, report evidence from Nepal showing that access to food markets may attenuate the negative effects of climate shocks. The underlying idea is that heat waves negatively impact food security, especially for households that consume from their own production or from very local production. In this regard, living in cities (i.e., urban residence) allows households to diversify food sources through access to food markets and may help mitigate the negative effects of heat waves.[26] In our data, we do not have good indicators of food availability during gestation and we use an interaction term between heat waves and a dichotomous indicator for urban residence.

The results are reported in panel (a) of Table 5. Although children in urban households fare better in terms of both weight and height outcomes, we do not find any significant interaction between heat waves and urban residence in the SSA context.

Another indirect way in which we can test the relevance of the food channel is by exploring the interplay between exposure to heat waves and the number of older siblings. Indeed, the number of siblings at the time of gestation could negatively impact the per

[25] In the Appendix, we also discuss the main differences in results compared to Wilde et al. (2017) and Davenport et al. (2020), who instead find some evidence of fetal selection.

[26] However, effects may also go in the opposite direction; indeed, food scarcity may increase food prices and particularly harm those who cannot live from their own production.

capita resources available to family members (*resource-dilution* effect) or the need to provide food to the already-born children may reduce the amount of food available to adult family members, including a pregnant mother. However, in panel (b) of Table 5 we do not find evidence in support of this hypothesis. The interaction coefficient between heat wave shocks and the number of older siblings is always nonsignificant.[27]

In general, there is no clear evidence in the extant research that food insecurity and poor nutrition are the main mechanisms through which in-utero heat shocks affect maternal and child health. Grace et al. (2015), for instance, do not find stronger effects for the Agriculturalists country group, where one would expect the food channel to be more important. A recent study finds a positive effect of exposure to extreme heat on infant mortality for India (Banerjee and Maharaj, 2020), which the authors explain through physiological impacts (i.e., incidence of diarrhea) and the impact of heat on food insecurity. As for the latter, only indirect evidence is provided by the authors, who demonstrate the negative effects of heat shocks on crop yields and the real wages of male workers. However, when the authors examine the interplay between heat shocks and two programs that had very different scopes—a public workfare program aimed at increasing household income (and indirectly, access to food) and a health intervention program aimed at improving both prenatal and postnatal care and health-related information—only the latter is found to attenuate the impact of temperature shocks on child mortality.

It is worth noting that information on household food availability during pregnancy is not directly available in the DHS, and it is difficult to find good proxies for food insecurity, especially if one is interested in the effect of heat wave exposure for the whole gestation (not only around conception) and given the delays that characterize the time at which shocks materialize and when their effects are observed in food markets. For instance, even heat waves before conception may have important effects on food availability during pregnancy. For this reason, we conclude that dismissing the importance of the food channel would require further research.

[Table 5 around here]

6.2 Infectious diseases: access to improved water or sanitation

A potential mediating factor for the negative effects of heat waves may be the prevalence of infectious diseases (e.g., diarrhea). Thus, we test whether the availability of improved water or sanitation reduces the negative effects of heat waves. We classify water sources as "improved water following the World Bank's definition: water piped into dwelling, piped into yard/plot, piped to neighbor's house, borehole with pump, protected well, protected spring, and bottled water. We define improved sanitation as a flush toilet, septic tank, piped sewer system, flush to open pit, compositing toilet, a ventilated improved pit latrine, a pit latrine with a slab. A household is classified as having an improved toilet if, for instance, the toilet is used only by members of one household and if the facility used by the household separates waste from human contact (WHO and UNICEF, 2014). Limited access to improved water and sanitation potentially exposes individuals to fatal diseases.

[27] The number of older siblings is omitted from the regressions since it is perfectly collinear with child birth order.

We build an aggregate indicator for whether the household has access to improved water or improved sanitation (WS) and interact it with exposure to heat waves. The results are reported in panel (a) of Table 6. Although access to water or sanitation generally improves most child health outcomes, the sign of the interaction with heat waves is generally counterintuitive (it seems to increase the harm produced by heat waves) but is statistically nonsignificant, except in two cases.

A potential weakness of this analysis is that the information on the availability of a household's potential adaptation strategies refers to the time of the interview and may therefore be affected by measurement error. Thus, in panel (b) of Table 6, availability of improved water or sanitation is proxied by the proportion of households having access to it at the district level.[28] However, also in this case improved water and sanitation is not significantly associated with a reduction in the effect of heat waves.

[Table 6 around here]

6.3 Heat stress: improved housing

Some house characteristics may reduce heat stress. In our data, housing features are classified as natural, rudimentary, or finished. Following Florey and Taylor (2016), improved flooring is categorized as having a rudimentary (i.e., tablets, mat, adobe) or finished floor (i.e., parquet, carpet, cement, bricks). Improved wall is considered as having a finished wall (i.e., covered adobe, bricks, cement blocks, wood planks). Improved roof is considered as having a finished roof (i.e., metal, wood, ceramic tiles, cement, roofing shingles). Based on these categories, we define improved housing as having improved floor, wall, and roof construction, while unimproved housing is a composite of unimproved floor, wall, and roof construction. In the model in panel (a) of Table 7, we include an interaction term between heat wave exposure and having improved housing and building materials. Because data on improved housing is not available in all waves, the sample size falls by about 50,000 observations. Although access to improved housing is positively associated with better child health outcomes, the coefficients for heat waves and the interaction term are often counterintuitive. For instance, the effect of heat waves on birth weight appears to be negative for households living in improved housing and positive for those not living in improved housing.

The analysis in panel (b) uses the proportion of households with access to improved housing (computed at the district level on all DHS surveys) and allows us to increase the sample size by using observations from waves in which individual improved housing is not available. This time, we find the usual positive effect of heat waves on severe stunting, while the interaction term is often of the expected sign (i.e., it attenuates the negative health effects of heat waves) but statistically nonsignificant.

[Table 7 around here]

[28] In order to compute prevalence on a sufficient number of observations, we take the average value in all DHS surveys. The same is done for other adaptation strategies in the next sections. In this specification, the non-interacted effect of improved water or sanitation is controlled for *de facto* by the district-month fixed effects.

6.4 Heat stress and infectious diseases: electricity

The availability of electricity to the household may provide additional adaptation strategies, e.g., access to air conditioning. In panel (a) of Table 8, we include an interaction term between heat wave exposure and a household's access to electricity, while in panel (b) we build the interaction term using average access to electricity at the district level. In neither of the two cases do we find evidence of important interactions between access to electricity and heat waves, although household-level access to electricity is generally associated with better child health.

[Table 8 around here]

6.5 Health-seeking behavior during pregnancy and prenatal care

A study from Colombia shows that mothers who are affected by heat shocks during gestation engage more intensively in health-seeking behavior for their children (Carrillo et al., 2016). In contrast, Molina and Saldarriaga (2017) document negative effects of heat shocks on the probability of medical assistance at childbirth in the Andean region.

On the one hand, compensatory parental behavior might explain the lack of significant negative effects of high temperatures on child health. On the other hand, improved access to prenatal care may represent an effective adaptation strategy (cf. Banerjee and Maharaj, 2020).

We test for compensatory behaviors by regressing the number of antenatal visits, institutional delivery, and medical assistance at childbirth on a child's exposure to heat waves while in utero. We define medical assistance during delivery as an indicator equal to one if the assistance came from a doctor, nurse, or community health assistant and zero otherwise. Regarding institutional delivery, we define it an indicator equal to one when delivery took place in a hospital or any approved medical center and zero otherwise. "Prenatal check-ups" are the number of visits to the hospital for medical care during pregnancy. Results are presented in panel (a) of Table 9 and indicate no significant effect of exposure to heat waves on prenatal care. However, when we analyze whether effects are different by maternal education, we find that low-educated mothers are likely to increase prenatal check-ups by 0.19 visits (about 4%) if they are exposed to heat waves during pregnancy. This finding may appear counterintuitive at first glance, as we would have expected highly educated mothers to invest more in child health. However, it can be explained by the fact that the demand for child health by highly educated mothers is greater at the baseline. Indeed, highly educated mothers demand 6.75 check-ups in the absence of heat waves, against 4.69 for low-educated mothers.

The effectiveness of increased prenatal care as a potential adaptation mechanism is directly tested in Table 10, in which we include an interaction term between in-utero heat waves and the number of prenatal visits (standardized to have mean zero and unit standard deviation). It must be noted that prenatal visits may be endogenous, i.e., represent a parental response to heat waves, as the results in Table 9 demonstrate. Antenatal check-ups are significantly associated with birth weight and the probability of low birth weight, with a 43.48 g increase and a 1.1 pp decrease, respectively, for a one-standard deviation (1σ hereafter) increase in the number of visits. Interestingly, the estimates also show that at the sample mean of prenatal visits, in-utero heat waves significantly increase the probability of the child being underweight (1.7 pp), stunted (1.8 pp), and severely stunted (1.6 pp), and reduces child HAZ (−0.06 standard deviations). Although the sample size drops from 134,810 to 81,509, the magnitude of the effect on severe stunting remains the same as in the full sample. Increased use of prenatal care is, on the other hand, associated with a reduction in the negative effects of heat shocks on child weight outcomes. For a 1σ increase in the number of check-ups, the probability of the child being underweight and severely underweight is reduced by −0.9 and −0.6 pp, respectively. In these estimates prenatal care, in contrast, does not appear to significantly improve severe stunting.

In order to address potential endogeneity issues related to the number of prenatal care visits, in Table 11 we report instrumental variables (IVs) estimates using (current) proximity to health facilities (available in the DHS) as an excluded instrument. The two potentially endogenous variables are the number of prenatal care visits and its interaction with heat waves in utero, which are instrumented with an indicator for having difficulties accessing health facilities and its interaction with in-utero heat waves, respectively. Since proximity to health facilities is only available for a sub-sample of observations, estimation samples are smaller. In the IVs estimates, we find significant negative effects of in-utero heat shocks on WAZ, underweight, severe underweight, HAZ, stunting, and severe stunting. Prenatal check-ups improve both WAZ and HAZ. Interestingly enough, prenatal check-ups are particularly beneficial to child health during heat waves. Increasing the number of prenatal check-ups by 1σ at the sample mean completely offsets all negative impacts of in-utero exposure to heat waves.

These last results confirm earlier findings by Banerjee and Maharaj (2020) for India, which show that a community healthcare worker program was associated with greater antenatal care, greater postnatal care, and a greater provision of important healthcare information to mothers, and that it was particularly effective at reducing the negative effects of heat shocks on child mortality. It is indeed likely that during antenatal check-ups pregnant mothers receive treatments for heat-induced diseases and physiological stress, along with useful information on effective behaviors to limit the harmful effects of heat waves on the unborn child.

[Table 9 around here]

[Table 10 around here]

[Table 11 around here]

7 Concluding remarks

Climate change is impacting several aspects of human activity and is likely to affect human health. This paper is an attempt to add to the extant literature on the adverse effects of increasing temperatures on the health conditions of children in Africa. We use several geo-referenced waves of the Demographic and Health Surveys for 20 Sub-Saharan countries over the period of 1990 to 2016 merged with gridded monthly data on the presence of heat waves and their magnitude since the 1980s to investigate the effects of heat shocks during gestation on children's health outcomes at birth and in their first five years of life.

Using a novel indicator of heat shocks (the Heat Wave Magnitude Index daily), among a wide range of child health outcomes including child height, weight, anemia, birth weight, and infant mortality we only find robust evidence of a positive and significant effect of prenatal exposure to heat waves on the probability of a child being severely stunted, which increases by 1.4 pp (8% from a baseline of 16.5% of children suffering from severe stunting). Analysis of heat wave exposure by trimester of gestation points to a larger effect on child height outcomes in the first and second trimesters and on birth weight in the second and third trimesters (−23 g.). Moreover, the negative effects on stunting are present for all heat wave intensity categories, although they are larger for heat waves with an intensity greater than 9.

Our analysis of the potential mechanisms does not point to food insecurity as the main explanation for the observed negative effects, possibly due to some data limitations. The analysis of the main adaptation strategies that may be available to households to cope with the other negative effects of heat waves (i.e., heat stress and infectious diseases), such as access to electricity, improved housing, and improved water and sanitation access, do not appear to be particularly effective in the SSA context. By contrast, our analysis suggests that (low-educated) future mothers tend to increase prenatal healthcare in the presence of a heat wave and that better access to prenatal care may help reduce the negative effects of in-utero heat shocks on children.

Our study contributes to the extant literature in a number of ways. First, by focusing on SSA we recognize the importance of addressing the health effects of heat shocks in a region that is both susceptible to extreme temperatures and lacks adequate adaptation strategies. Second, we employ a number of health outcomes (both short- and long-term) that might be affected by heat wave exposure, whereas past studies concentrated on only one or few outcomes, such as mortality or birth weight. Third, in our empirical analysis we use a new indicator of heat waves (Russo et al., 2015) that has been empirically validated (e.g., by comparison with media coverage of extreme heat events) and gathers information both on the length and intensity of heat episodes, overcoming some of the limitations of indicators that have been used in the past literature. Finally, we report a thorough analysis of the potential adaptation strategies that may help reduce the negative consequences of heat waves on babies' and infants' health in SSA.

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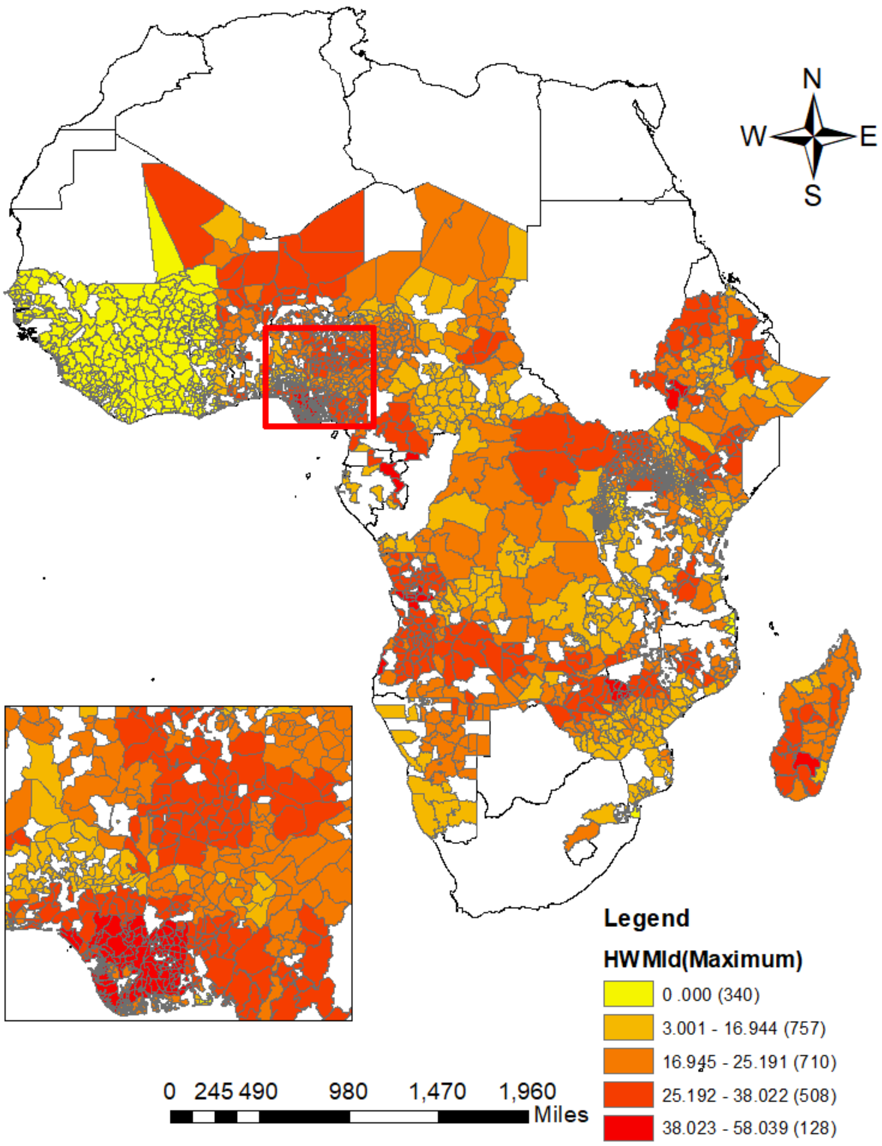
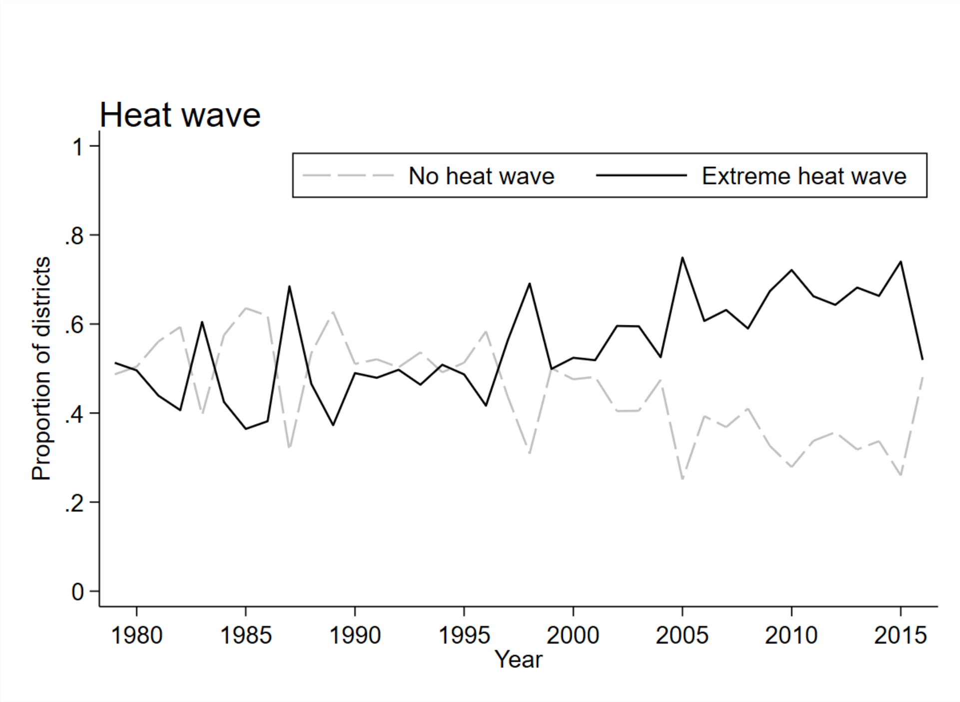
Figures and Tables

Figure 1: Maximum heat wave magnitudes by district (1979–2016)



Notes: The figure shows the maximum HWMId computed according to Russo et al. (2014) for districts in SSA in the 1979–2016 period. Areas depicted in white either do not belong to SSA or are excluded from the analysis owing to heat wave data unavailability. In brackets, we report the number of districts in each category.

Figure 2: Trend of heat waves in Sub-Saharan Africa



Notes: The figure shows the proportion of districts in SSA countries with no heat shock ($HWMId = 0$) and with extreme heat waves ($HWMId > 3$) for the period spanning 1979–2016. Source: Authors' own calculations based on the Global Administrative Areas (GADM) version 2.6 Heat Wave Magnitude Index (Russo et al., 2014).

Table 1: Sample descriptive statistics

	Stayers			All		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	N. obs.	mean	sd	N. obs.	mean	sd
Health outcomes						
Weight-for-age z-score (WAZ)	134,810	-0.96	1.36	268,535	-0.92	1.34
Undernutrition (WAZ < -2)	134,810	20.18		268,535	18.91	
Severe undernutrition (WAZ < -3)	134,810	6.78		268,535	6.14	
Height-for-age z-score (HAZ)	134,810	-1.48	1.80	268,535	-1.45	1.79
Stunting (HAZ < -2)	1348,10	38.76		268,535	37.53	
Severe stunting (HAZ < -3)	134,810	18.03		268,535	17.36	
Anemia ($<$ 11 g./dL)	43,861	60.37		99,393	58.20	
Birth weight (g.)	61,215	3,220.63	637.21	128,354	3,223.97	641.15
Low birth weight ($<$ 2500 g.)	61,215	7.87		128,354	7.92	
Heat waves						
Heat Wave Magnitude Index daily (HWMId)	134,810	1.42	2.65	268,535	1.54	2.70
$HWMId = 0$	134,810	0.53		268,535	0.49	
$0 < HWMId \leq 3$	134,810	0.30		268,535	0.32	
$3 < HWMId \leq 6$	134,810	0.11		268,535	0.12	
$6 < HWMId \leq 9$	134,810	0.03		268,535	0.04	
$HWMId > 9$	134,810	0.03		268,535	0.03	
Heat wave 1st term	134,810	0.66		268,535	0.70	
Heat wave 2nd term	134,810	0.67		268,535	0.71	
Heat wave 3d term	134,810	0.66		268,535	0.70	
Control variables						
Mother's age at childbirth	134,810	27.26	6.74	268,535	26.92	6.64
Mother's current age	134,810	29.04	6.90	268,535	28.81	6.80
Mother's education: none	134,810	0.36		268,535	0.33	
Mother's education: primary	134,810	0.41		268,535	0.40	
Mother's education: secondary	134,810	0.21		268,535	0.24	
Mother's education: tertiary	134,810	0.02		268,535	0.03	
Christian	134,810	0.63		268,535	0.65	
Urban residence	134,810	0.26		268,535	0.29	
Child characteristics						
Age in months	134,810	26.45	16.95	268,535	27.72	17.09
Male	134,810	0.50		268,535	0.50	
Birth order	134,810	3.88	2.45	268,535	3.62	2.39
Birth year	134,810	2002.86	7.27	268,535	2005.68	6.63

Notes: Authors' calculations using the Demographic and Health Surveys (DHS Program, USAID). Statistics in columns (1)–(3) refer to the estimation sample only including "stayers" (i.e., women who did not change residence since pregnancy), which is used in Table 2, while columns (4)–(6) refer to all individuals in the selected DHS waves. The number of observations differs according to the availability of the different variables in each wave used in our analysis. The standard deviation (sd) is only reported for continuous variables. Dichotomous health outcomes are multiplied by 100; accordingly, regression coefficients represent percentage-point changes.

Table 2: Effects of heat waves during pregnancy on child health

Child outcomes	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
(a) Country and birth month FEs									
Heat wave in utero	0.001	0.843	0.530	-0.027	1.193	1.669***	0.544	-7.202	0.156
	(0.029)	(0.651)	(0.404)	(0.032)	(0.764)	(0.581)	(2.054)	(11.119)	(0.514)
(b) Country-year and country-birth month FEs									
Heat wave in utero	-0.053**	2.352***	0.955**	-0.070**	2.082**	2.341***	0.268	-9.708	0.217
	(0.027)	(0.675)	(0.372)	(0.029)	(0.805)	(0.589)	(1.839)	(11.609)	(0.591)
(c) Country-year and region-birth month FEs									
Heat wave in utero	0.004	0.720	0.016	-0.031	1.050	1.382***	-0.004	-7.811	0.298
	(0.029)	(0.716)	(0.362)	(0.026)	(0.721)	(0.480)	(1.606)	(11.656)	(0.635)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,215	61,215
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.
Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients are in percentage points . The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise. Control variables include sex of the child, mothers literacy status, mother's educational level, child's birth order, age of child in months, religion (indicator for Christianity), place of residence (indicator for urban residence), and maternal age at birth. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 3: Effects of heat waves during pregnancy on child health by trimester of gestation

Child outcomes	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
				(a) Trimester heat wave indicators					
Heat wave trim. 1	0.004	-0.132	0.196	-0.017	0.517	0.504	0.600	0.598	0.276
	(0.011)	(0.324)	(0.193)	(0.014)	(0.441)	(0.313)	(0.885)	(7.969)	(0.275)
Heat wave trim. 2	0.006	0.230	-0.181	-0.013	0.456	0.030	-1.330	-13.560	-0.222
	(0.013)	(0.348)	(0.206)	(0.019)	(0.417)	(0.353)	(0.816)	(8.368)	(0.354)
Heat wave trim. 3	-0.001	-0.329	0.044	0.007	-0.059	0.032	-0.631	-12.244*	0.620*
	(0.015)	(0.423)	(0.224)	(0.017)	(0.427)	(0.382)	(0.734)	(7.014)	(0.341)
				(b) Combined trimester heat wave indicators					
Heat wave trim. 1	0.013	0.966	0.139	-0.020	0.969	1.753***	1.835	3.341	-0.108
	(0.030)	(0.682)	(0.473)	(0.040)	(0.921)	(0.662)	(1.787)	(19.128)	(0.825)
Heat wave trim. 2	-0.034	2.498**	0.051	-0.074*	2.040*	1.988**	-0.330	2.009	-0.277
	(0.041)	(1.076)	(0.589)	(0.041)	(1.042)	(0.836)	(2.699)	(16.855)	(0.862)
Heat wave trim. 3	-0.006	0.725	0.158	-0.023	0.799	1.021	1.395	-2.455	0.516
	(0.033)	(0.812)	(0.433)	(0.031)	(0.899)	(0.625)	(1.794)	(15.013)	(0.806)
Heat wave trim. 1, 2	0.016	0.393	-0.091	-0.046	1.290	1.371**	-0.260	-6.040	0.124
	(0.030)	(0.804)	(0.433)	(0.031)	(0.871)	(0.592)	(1.844)	(15.080)	(0.762)
Heat wave trim. 2, 3	0.019	0.213	-0.345	-0.006	0.465	1.045*	-1.959	-23.092*	0.312
	(0.037)	(0.965)	(0.493)	(0.033)	(0.941)	(0.620)	(1.700)	(13.643)	(0.756)
Heat wave trim. 1, 3	-0.002	0.040	0.090	-0.034	0.864	1.745***	-0.478	-3.997	1.049
	(0.035)	(0.878)	(0.500)	(0.033)	(0.937)	(0.668)	(2.006)	(16.712)	(0.734)
Heat wave trim. 1, 2, 3	0.005	0.462	0.095	-0.037	1.353*	1.243**	-0.693	-20.689	0.580
	(0.029)	(0.803)	(0.390)	(0.027)	(0.765)	(0.602)	(1.811)	(12.889)	(0.685)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients are in percentage points. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave during the given trimester (or combination of trimesters) of gestation and zero otherwise. The control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 4: Effects of heat waves during pregnancy on child health by HWMId intensity category

Child outcomes	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
Heat wave intensity bins									
[0, 3]	-0.000	0.800	0.029	-0.027	0.955	1.412***	0.461	-12.657	0.467
	(0.029)	(0.693)	(0.360)	(0.026)	(0.709)	(0.502)	(1.606)	(12.246)	(0.632)
(3,6]	0.021	0.349	-0.032	-0.026	1.047	1.284**	0.173	-0.084	0.124
	(0.032)	(0.813)	(0.402)	(0.036)	(0.935)	(0.608)	(1.731)	(13.527)	(0.718)
(6,9]	-0.000	0.996	0.003	-0.063*	1.481	1.254**	-2.104	-6.712	-0.234
	(0.032)	(0.874)	(0.475)	(0.033)	(0.911)	(0.601)	(1.877)	(14.899)	(0.673)
>9	-0.021	1.259	0.174	-0.063	1.974*	1.852**	-2.373	12.365	0.104
	(0.044)	(1.107)	(0.617)	(0.041)	(1.100)	(0.767)	(1.990)	(16.156)	(0.833)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients are in percentage points . The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave of a given intensity category during gestation and zero otherwise. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 5: Heat waves and child health: food insecurity

Child outcome	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
					(a) Urban residence				
Heat wave in utero (HW) (α_0)	0.007	0.311	-0.215	-0.020	0.557	1.053*	-1.205	6.744	0.172
	(0.029)	(0.815)	(0.463)	(0.028)	(0.746)	(0.609)	(1.706)	(14.452)	(0.952)
HW × urban residence (α_1)	-0.008	1.368	0.775	-0.035	1.651	1.099	3.783	-30.822	0.267
	(0.038)	(0.992)	(0.636)	(0.036)	(1.066)	(0.820)	(3.146)	(19.491)	(1.049)
Urban residence	0.210***	-5.996***	-2.892***	0.284***	-7.666***	-5.325***	-6.286**	26.552	-0.542
	(0.036)	(0.906)	(0.546)	(0.034)	(1.019)	(0.821)	(3.040)	(19.704)	(0.923)
Coef. $\alpha_0 + \alpha_1$	-0.001	1.679*	0.559	-0.056	2.207*	2.151***	2.578	-24.08	0.439
p-value	0.980	0.086	0.260	0.142	0.056	0.001	0.392	0.133	0.502
					(b) N. older siblings				
Heat wave in utero (HW)	0.004	0.717	0.019	-0.031	1.045	1.379***	-0.019	-7.416	0.345
	(0.029)	(0.715)	(0.360)	(0.026)	(0.725)	(0.481)	(1.609)	(11.731)	(0.626)
HW × no. older sib.	-0.001	0.118	-0.095	-0.002	0.207	0.116	-0.380	2.416	0.287
	(0.012)	(0.398)	(0.252)	(0.012)	(0.450)	(0.278)	(1.059)	(11.096)	(0.447)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with urban residence (panel (a)) or number of older siblings (panel (b)). Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes. The number of older siblings is *de facto* controlled for by birth-order indicators.

Table 6: Heat waves and child health: access to improved water and sanitation

Child outcome	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
(a) Individual access to improved water and sanitation									
Heat wave in utero (HW)	0.005	0.654	-0.027	-0.022	0.895	1.170**	-0.748	-6.214	0.125
	(0.028)	(0.699)	(0.368)	(0.027)	(0.742)	(0.493)	(1.617)	(11.856)	(0.675)
HW × WS	0.006	0.147	0.163	-0.034	0.534	0.987*	3.130*	-4.510	0.538
	(0.025)	(0.680)	(0.426)	(0.028)	(0.718)	(0.548)	(1.594)	(12.515)	(0.460)
Access to improved water (W)	0.032	-0.776	-0.065	0.074***	-2.226***	-1.725***	-1.222	6.541	-0.407
	(0.020)	(0.514)	(0.364)	(0.016)	(0.511)	(0.433)	(0.803)	(9.037)	(0.380)
Access to improved sanitation (S)	0.118***	-2.500***	-1.009**	0.165***	-3.876***	-2.619***	-4.087***	33.865***	-1.402***
	(0.021)	(0.592)	(0.405)	(0.029)	(0.721)	(0.552)	(1.277)	(11.777)	(0.471)
(b) District-level prevalence of improved water and sanitation									
Heat wave in utero (HW)	0.004	0.742	0.022	-0.031	1.087	1.384***	0.096	-4.950	0.232
	(0.029)	(0.725)	(0.365)	(0.026)	(0.742)	(0.483)	(1.639)	(11.946)	(0.660)
HW × prevalence WS	-0.012	0.582	0.153	-0.009	0.947	0.071	-0.908	-9.644	0.224
	(0.023)	(0.461)	(0.292)	(0.027)	(0.844)	(0.507)	(0.937)	(6.535)	(0.426)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5%level; *** at the 1%level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with individual access to improved water and sanitation or the prevalence of improved water or sanitation at the district level—in panels (a) and (b), respectively. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 7: Heat waves and child health: access to improved housing

Child outcome	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
				(a) Individual access to improved housing					
Heat wave in utero (HW)	0.041	0.402	-0.343	-0.008	1.974	0.924	0.814	39.868**	0.111
	(0.029)	(0.916)	(0.521)	(0.047)	(1.397)	(0.833)	(2.028)	(15.828)	(1.103)
HW × improved housing	-0.028	0.280	-0.625	-0.072	-0.662	-0.910	-1.658	-76.297***	-0.214
	(0.062)	(1.661)	(1.028)	(0.078)	(2.022)	(1.113)	(2.198)	(26.777)	(1.054)
Improved housing	0.194***	-3.660**	-1.082	0.235***	-4.058**	-2.200**	0.420	72.555**	-0.128
	(0.062)	(1.618)	(0.876)	(0.078)	(2.042)	(1.042)	(2.054)	(27.876)	(1.064)
Observations	81,051	81,051	81,051	81,051	81,051	81,051	37,647	42,723	42,723
Mean of dep. var.	-0.913	17.73	5.622	-1.203	31.46	12.65	61.20	3124	9.663
				(b) District-level prevalence of improved housing					
Heat wave in utero (HW)	0.003	1.076	0.090	-0.025	1.508**	1.552**	0.924	-1.594	0.262
	(0.035)	(0.927)	(0.403)	(0.030)	(0.748)	(0.597)	(1.910)	(12.784)	(0.688)
HW × prevalence improved housing	0.057*	-0.997	-0.688*	0.018	-0.653	-0.470	-0.755	-12.325	-0.282
	(0.029)	(0.664)	(0.391)	(0.030)	(0.882)	(0.505)	(1.353)	(9.682)	(0.485)
Observations	108,630	108,630	108,630	108,630	108,630	108,630	38,008	53,755	53,755
Mean of dep. var.	-0.953	18.52	5.831	-1.350	34.81	14.70	61.58	3173	8.643

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with individual access to improved housing or the prevalence of improved housing at the district level—in panels (a) and (b), respectively. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 8: Heat waves and child health: access to electricity

Child outcome	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
				(a) Individual access to electricity					
Heat wave in utero (HW)	0.004	0.531	0.058	-0.013	0.462	1.153**	-1.080	1.626	0.254
	(0.028)	(0.773)	(0.400)	(0.027)	(0.740)	(0.578)	(1.806)	(13.863)	(0.807)
HW × electricity	0.003	0.805	-0.228	-0.078*	2.610	0.998	4.511*	-28.967	0.149
	(0.057)	(1.557)	(0.891)	(0.047)	(1.599)	(1.001)	(2.511)	(23.897)	(1.032)
Electricity	0.178***	-4.560***	-1.786**	0.282***	-8.161***	-3.984***	-7.308***	57.818**	-1.013
	(0.058)	(1.595)	(0.719)	(0.055)	(1.631)	(1.012)	(2.696)	(24.221)	(0.950)
				(b) District prevalence of access to electricity					
Heat wave in utero (HW)	-0.000	0.796	0.056	-0.033	1.061	1.416***	0.179	-5.412	0.298
	(0.025)	(0.661)	(0.341)	(0.024)	(0.687)	(0.466)	(1.633)	(11.707)	(0.650)
HW × prevalence electricity	0.044*	-0.770	-0.401	0.026	-0.108	-0.349	-1.272	-8.508	0.001
	(0.024)	(0.570)	(0.298)	(0.026)	(0.828)	(0.395)	(1.121)	(7.294)	(0.507)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.
Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with individual access to electricity or the prevalence of access to electricity at the district level—in panels (a) and (b), respectively. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 9: Heat waves and child health: health seeking behavior

Outcomes	(1) Prenatal check-ups	(2) Institutional delivery	(3) Medical assistance at birth
	(a) Baseline		
Heat wave in utero	0.110	-0.311	0.596
	(0.078)	(0.563)	(0.795)
	(b) Heterogeneous effects by maternal education		
Heat wave in utero (HW) (α_0)	0.186***	-0.510	0.402
	(0.064)	(0.534)	(0.725)
HW $\times$ high maternal education (α_1)	-0.289	0.969	0.955
	(0.188)	(1.694)	(2.136)
Coef. $\alpha_0 + \alpha_1$	-0.103	0.460	1.357
p-value	0.610	0.779	0.527
Observations	81,509	133,229	72,968
Mean of dep. var.	5.14	53.62	56.61
Mean of dep. var. high education	6.75	82.95	83.46
Mean of dep. var. low education	4.69	47.21	51.1

* Significant at the 10% level level; ** at the 5% level; *** at the 1% level.
Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. Outcomes in columns 2 and 3 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficients of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with maternal education (panel (b)). Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 10: Heat waves and child health: interaction with prenatal check-ups (OLS)

Child outcome	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
Heat wave in utero (HW)(α_0)	-0.037	1.730***	0.273	-0.064**	1.787**	1.625***	0.391	-18.646	0.637
	(0.031)	(0.648)	(0.407)	(0.030)	(0.899)	(0.546)	(2.236)	(15.111)	(0.748)
HW $\times$ prenatal check-ups (α_1)	0.048***	-0.869***	-0.555**	0.018	-0.113	-0.070	-0.371	-8.209	0.081
	(0.014)	(0.293)	(0.248)	(0.024)	(0.646)	(0.388)	(1.747)	(10.740)	(0.441)
Prenatal check-ups	-0.004	-0.000	0.357	0.049*	-1.263*	-0.688*	-0.403	43.479***	-1.145***
	(0.017)	(0.295)	(0.252)	(0.027)	(0.738)	(0.399)	(1.557)	(12.843)	(0.358)
Coef. $\alpha_0 + \alpha_1$	0.0114	0.860	-0.282	-0.0461	1.674	1.555**	0.0202	-26.85	0.719
p-value	0.732	0.242	0.534	0.246	0.154	0.0181	0.995	0.169	0.357
Observations	81,509	81,509	81,509	81,509	81,509	81,509	29,134	46,645	46,645
Mean of dep. var.	-0.938	18.98	6.428	-1.188	30.86	12.76	68.22	3170	8.259

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with the standardized number of prenatal check-ups (with zero mean and unit standard deviation). Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

Table 11: Heat waves and child health: interaction with prenatal check-ups (IVs)

VARIABLES	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
Heat wave in utero (HW)(α_0)	-0.162**	5.666***	2.583**	-0.204*	7.599***	4.331**	0.275	-6.472	-0.110
	(0.077)	(2.107)	(1.198)	(0.106)	(2.252)	(2.136)	(2.256)	(88.651)	(3.271)
HW × prenatal check-ups (α_1)	0.257*	-10.186***	-4.339*	0.177	-9.667*	-5.298	-15.385	-15.130	0.974
	(0.148)	(3.828)	(2.474)	(0.224)	(5.642)	(4.719)	(16.843)	(172.062)	(6.292)
Prenatal check-ups	0.321*	2.216	-3.729	0.501**	-1.742	-4.362	3.162	24.704	-2.676
	(0.172)	(4.635)	(2.790)	(0.247)	(6.209)	(4.396)	(14.233)	(148.936)	(6.854)
Coef. $\alpha_0 + \alpha_1$	0.0950	-4.520	-1.756	-0.0269	-2.068	-0.967	-15.11	-21.60	0.864
p-value	0.357	1	0.348	1	1	1	1	1	0.804
Observations	57,474	57,474	57,474	57,474	57,474	57,474	29,131	35,965	35,965
Mean of dep. var.	-0.683	13.51	4.091	-1.045	27.53	11.66	68.22	3180	8.968
1st stage F-stat. (N. visits)$^{(a)}$	27.19	27.19	27.19	27.19	27.19	27.19	21.84	13.61	13.61
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1st stage F-stat. (N. visits#HW)$^{(a)}$	17.49	17.49	17.49	17.49	17.49	17.49	24.75	12.62	12.62
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with the standardized number of prenatal check-ups (with zero mean and unit standard deviation) both estimated with instrumental variables (IVs). The excluded instruments are a dichotomous indicator for having difficulties to access health facilities and its interaction with in-utero exposure to heat waves. Control variables as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of health outcomes.

$^{(a)}$ Sanderson–Windmeijer multivariate F-test of excluded instruments.

A Appendix: Additional tables

Table A1: List of surveys in the DHS

Country	Waves	Number of regions
Angola	2015, 2016	18
Benin	1996, 2001	6
Burkina Faso	1993, 1998, 1999, 2003	4
Cameroon	1991, 2004	10
Congo D.R	2007	9
Ghana	1993, 1994, 1998, 2003, 2008	2
Kenya	2003, 2008, 2009	8
Madagascar	1997	6
Malawi	2000, 2001, 2015, 2016	3
Mali	1995, 1996, 2001, 2006	2
Namibia	2000, 2006, 2007	13
Niger	1992, 1998	8
Nigeria	1990, 2003, 2008	6
Rwanda	2005	5
Swaziland	2006, 2007	4
Tanzania	1999, 2015, 2016	25
Togo	1998	5
Uganda	2000, 2001, 2006	10
Zambia	2007, 2013, 2014	10
Zimbabwe	1999, 2005, 2006, 2015	10

Notes: This table reports the list of country and DHS waves included in our empirical analysis.

Table A2: Effects of heat waves during pregnancy on child health, controlling for precipitation

Child outcomes	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
Heat wave in utero	0.005	0.696	-0.023	-0.031	1.048	1.394***	0.119	-7.693	0.282
	(0.029)	(0.729)	(0.371)	(0.026)	(0.724)	(0.479)	(1.611)	(11.743)	(0.639)
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0). The number of observations varies across columns depending on the availability of the health outcomes.

Table A3: Effects of heat waves during pregnancy on child health: heterogeneous effects

Child outcomes	(1) WAZ	(2) WAZ<2	(3) WAZ<3	(4) HAZ	(5) HAZ<2	(6) HAZ<3	(7) Anemia	(8) BW	(9) LBW
				(a) Heterogeneity by mother's education					
Heat wave in utero (HW)	0.001	0.831	0.206	-0.024	0.953	1.515***	-0.982	-4.215	0.988
	(0.028)	(0.762)	(0.380)	(0.025)	(0.717)	(0.503)	(1.901)	(14.683)	(0.792)
HW × mother's high education	0.017	-0.542	-0.923	-0.031	0.473	-0.649	3.144	-10.005	-1.919*
	(0.044)	(1.188)	(0.664)	(0.052)	(1.717)	(0.993)	(2.291)	(23.652)	(1.119)
Coef. for mother's high edu.	0.018	0.289	-0.717	-0.055	1.426	0.866	2.162	-14.22	-0.931
p-value	0.721	0.802	0.256	0.318	0.403	0.363	0.284	0.450	0.269
				(b) Heterogeneity by child gender					
Heat wave in utero (HW)	0.013	0.906	-0.274	-0.032	1.003	1.173**	0.988	-3.306	0.749
	(0.034)	(0.853)	(0.483)	(0.029)	(0.820)	(0.510)	(1.874)	(16.529)	(0.756)
HW × boy	-0.018	-0.370	0.575	0.002	0.093	0.414	-1.964	-8.961	-0.896
	(0.027)	(0.734)	(0.588)	(0.027)	(0.675)	(0.559)	(2.149)	(18.110)	(0.761)
Coef. for boy	-0.005	0.537	0.301	-0.03	1.096	1.587***	-0.975	-12.27	-0.148
p-value	0.874	0.477	0.505	0.310	0.157	0.009	0.625	0.339	0.838
Observations	134,810	134,810	134,810	134,810	134,810	134,810	43,861	61,207	61,207
Mean of dep. var.	-1.088	22.61	7.969	-1.427	37.06	16.47	63.40	3178	8.467

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variables are indicated in the column headings. BW stands for birth weight and LBW for low birth weight. Outcomes in columns 2, 3, 5, 6, 7, and 9 are multiplied by 100 so that coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with mother's education (panel (a)) or child gender (panel (b)). Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId= 0). The number of observations varies across columns depending on the availability of health outcomes.

B Appendix: Selectivity issues

B.1 Fetal selection

Our estimates of the effect of heat wave exposure during pregnancy on child health outcomes may be affected by in utero selection (i.e., the probability that the child dies in the womb). Stronger and healthier fetuses are more likely to survive for the entire duration of pregnancy, while weaker ones may die because of heat wave shocks.

Direct investigation of fetal loss effects is difficult given the several biases existing in reporting fetal loss (recall bias, social desirability bias, under-reporting of fetal losses happening very early in the pregnancy). Moreover, the DHS does not distinguish between miscarriage, stillbirth, and voluntary abortion and has important inconsistencies in the reported calendar for terminated pregnancies (MacQuarrie et al., 2018). Probably for these reasons, previous studies of the effect of heat shocks on the probability of terminating a pregnancy have found conflicting results. Wilde et al. (2017) do not report any evidence of fetal selection effects in DHS data, which they explain with measurement error as pregnancy termination also captures voluntary abortions. By contrast, Davenport et al. (2020) report positive associations between being exposed to high temperatures and both miscarriage and stillbirth. The evidence is therefore mixed.

Indirect evidence on the fetal selection hypothesis can be provided by examining the effect of heat waves on child gender (cf. Wilde et al., 2017). According to the literature, heat wave shocks during pregnancy may affect the probability that the child is female because female fetuses are more resistant, i.e., a *culling* effect (Catalano et al., 2005; Catalano and Bruckner, 2006; Catalano et al., 2006; Liu et al., 2014). To investigate this effect, we regress a dummy variable for whether the child is female on heat wave exposure in the month of conception. The results are reported in Table B1. Column (1) shows the estimates for the full sample of children below the age of 6 at the time of the survey, while column (2) restricts the sample to children who are aged two or less at the time of the survey (cf. Wilde et al., 2017), in order to attenuate potential biases related to recall bias. In this case as in our main analysis, we only focus on "stayers" so as to attenuate measurement error. Exposure to heat waves *at conception* does not significantly increase the probability that the child is female. Our results differ from Wilde et al. (2017), who find that a one-degree-celsius increase in the average monthly temperature at conception increases the fraction of females born by 0.25 pp, using census data. A possible explanation is that the magnitude being not very large, compared to Wilde et al. (2017) (which does not restrict the sample to individuals alive and with anthropometric measures) our smaller estimation sample does not allow us to precisely estimate fetal selection effects. Therefore, we replicated the analysis also including "movers" and DHS surveys in which information on past residence is not available (in columns (3) and (4)). In this case, similarly to Wilde et al. (2017) we find a 11 pp positive effect on the sample of children below age 2. In columns (5)–(8), we replicate the same analysis using exposure to heat waves during the whole pregnancy. The coefficients are always *negative* (i.e., against a culling effect) and statistically nonsignificant. Thus, these findings run against the existence of strong fetal selection effects associated with heat shocks.

Table B1: Heat waves and the probability that the child is female

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Heat wave at conception	0.057	-0.005	0.030	0.107**				
	(0.057)	(0.085)	(0.039)	(0.051)				
Heat wave in utero					-0.267	-0.884	-0.218	-0.486
					(0.604)	(1.026)	(0.421)	(0.616)
Sample	Stayers	Stayers	All	All	Stayers	Stayers	All	All
Age group	< 6	≤ 2	< 6	≤ 2	< 6	≤ 2	< 6	≤ 2
Observations	176,483	84,057	423,203	184,565	176,483	84,057	423,203	184,565
Mean of dep. var.	49.71	49.78	49.43	49.43	49.88	49.96	49.56	49.51

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variable is an indicator variable that takes a value of one if the child is female and zero otherwise. The value is multiplied by 100, so the coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock at conception (columns (1)–(4)) or during gestation (columns (5)–(8)) and zero otherwise. Control variables include maternal literacy, level of education, urban residence, Christian religion, age, age at motherhood, and child birth order. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0).

B.2 Child mortality

We complement the analysis by examining post-birth selection through infant mortality. We do so by regressing the probability of child death at various months after birth, conditional on being born alive, on in-utero exposure to heat waves. While there are many studies on the effects of temperature shocks on adult mortality (see the review in Deschênes, 2014), evidence on infant mortality is much more sparse.[29]

Panel (a) of Table B2 restricts the analysis to the sample of "stayers", while in panel (b) we report the estimates in the full sample. In both cases, there is no clear evidence of post-birth selection owing to child mortality. Only in one case, in the sample of "stayers" and for mortality by age 6, exposure to heat waves is associated with a 0.5 pp higher probability of death. Our results are consistent with Wilde et al. (2017), who do not find higher mortality for children exposed to high temperatures at conception. In panel (c), we investigate differential mortality due to heat waves by maternal education. As highly educated mothers invest more in their children, including in child health (Currie and Moretti, 2003), maternal education may act as a protecting factor also with respect to weather shocks. However, we do not find any support for this hypothesis in the data.

[29] For Africa, Kudamatsu et al. (2016) find that infants born after droughts in arid climates or after unusually long spells of malarious weather in areas characterized by low malaria transmission have a higher probability of dying 0-12 months after birth.

Table B2: Heat waves and child mortality for various age groups

Death at age (in months)	(1) 0–11	(2) 12–23	(3) 24–35	(4) 36–47	(5) 48–59	(6) 0–59
			(a) Baseline			
Heat wave in-utero	0.117	0.305	0.986	-0.691	0.578	0.222
	(0.399)	(0.630)	(0.629)	(0.677)	(0.731)	(0.234)
Observations	89,550	87,312	85,603	81,906	78,692	423,089
Mean of dep. var.	4.956	7.444	9.183	11.97	10.51	8.749
			(b) interaction with maternal education			
Heat wave in utero (HW)(α_0)	-0.046	0.341	0.986	-0.889	0.156	0.085
	(0.409)	(0.689)	(0.703)	(0.676)	(0.857)	(0.264)
HW $\times$ mother's high education (α_1)	0.728	-0.156	0.000	0.854	1.502	0.616
	(0.602)	(0.709)	(1.087)	(0.945)	(1.138)	(0.435)
Coef. $\alpha_0 + \alpha_1$	0.682	0.185	0.986	-0.0351	1.658	0.701
p-value	0.277	0.798	0.317	0.973	0.0894	0.0701
Observations	89,550	87,312	85,603	81,906	78,692	423,089
Mean of dep. var.	4.956	7.444	9.183	11.97	10.51	8.749

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.
Notes: Robust standard errors clustered at the district level are in parentheses. In column (1), the sample contains children who were born less than 12 months before the interview and the dependent variable is an indicator variable that takes a value of one if the child is dead at the time of the interview. In column (2), the sample contains children who were born between 12 and 24 months before the interview and the dependent variable is an indicator variable that takes a value of one if the child died between 12 and 24 months. A similar procedure is followed for the 25–36, 37–48, 49–60, and 0–59 month ranges in columns (3), (4), (5), and (6), respectively. All indicators are multiplied by 100, so the coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise. Control variables are as in Table 2. All models include country-year and district-birth month FEs. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0) and is the same across panels.

B.3 Selection on fertility choices

Heat waves may influence women's proclivity to become pregnant. Intense heat stress may reduce sexual activity for both men and women (Lam and Miron, 1996; Barreca et al., 2014; Wilde et al., 2017), or couples that decide to conceive during heat waves may have characteristics that also affect future child health.

B.3.1 Sexual activity

We test whether sexual activity during periods of extreme heat waves is higher or lower, and if it is associated with maternal education. We create an indicator variable that is equal to one if a woman was sexually active in the four weeks preceding the survey. We then regress this variable on heat wave exposure in the previous month, in column (1) of Table B3, while in column (2) we also include an interaction term with maternal high education (secondary schooling or higher). Similarly to the models estimated for child health, district-month of interview and country-year of interview fixed effects are included in the regressions. Column (1) shows no significant interplay between heat waves and sexual activity. The results do not change when allowing for the effect to be heterogeneous by maternal education, in column (2). In contrast, Wilde et al. (2017) find a significant reduction in sexual activity associated with high temperatures. However, when we do replicate their specification—which includes separate year, month, and country-of-interview fixed effects—we find similar results to theirs: experiencing a heat wave in the month before the interview reduces sexual activity by 1.4 pp (column (3)), with a larger effect for more educated women (-2.5 pp in column (4)).

All in all, from our preferred specifications in columns (1) and (2), we conclude that there is no strong evidence of heat waves changing the frequency of women's sexual intercourse. This is consistent with recent evidence reported for the US by Barreca et al. (2018), who find that although hot days in the US tend to reduce birth rates 8 to 10 months later, the main mechanism is a reduction of reproductive health rather than reduced sexual activity. Similar conclusions, that sexual activity is unlikely to be the main explanation for the ambient temperature–birth rate nexus are drawn by Hajdu and Hajdu (2019) for Hungary.

B.4 Parental characteristics

A further way of testing the interplay between potential selection into parenthood and exposure to heat waves is to run models in which maternal education is regressed on the indicator for heat wave exposure.

The estimates in the sample of "stayers" in column (1) and in the full sample in column (2) show that children who were exposed to heat waves at conception are not less likely to have low-educated mothers (primary or lower). In columns (3) and (4), we split heat wave exposure at conception vs. in the other months of gestation. In this case as well, "children of heat waves" do not appear to be negatively selected in terms of socioeconomic background. Results are consistent with Wilde et al. (2017).

Table B3: Heat waves (HW) and probability of being sexually active in the previous four weeks

	(1)	(2)	(3)	(4)
Heat wave				
previous 4 weeks (HW4)(α_0)	0.273	0.507	-1.359*	-0.940
	(0.720)	(0.723)	(0.745)	(0.696)
HW4 $\times$ individual high education (α_1)		-0.758		-1.539*
		(0.714)		(0.908)
Coef. $\alpha_0 + \alpha_1$		-0.250		-2.479**
p-value		0.787		0.0318
District-month of interview FE	Yes	Yes		
Country-year of interview FE	Yes	Yes		
District FE			Yes	Yes
Interview year FE			Yes	Yes
Interview month FE			Yes	Yes
Observations	349,815	349,815	349,824	349,824
Mean of dep. var.	64.82	64.82	64.82	64.82

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variable is an indicator variable that takes a value one if the respondent was sexually active in the four weeks preceding the interview. The value is multiplied by 100, so the coefficients represent percentage point changes. High education indicates that the mother has secondary-level education or more. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock during gestation and zero otherwise, and its interaction with maternal education. Control variables include indicators for maternal literacy status and urban residence, mother's level of education, maternal current age, age at childbirth, and Christian religion. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0).

Table B4: Heat waves and mother's low education

	(1)	(2)	(3)	(4)
HW at conception	-0.012	-0.017	-0.013	-0.013
	(0.049)	(0.033)	(0.049)	(0.032)
HW months 2–9			0.283	-0.627
			(0.545)	(0.545)
Sample	Stayers	All	Stayers	All
District-Month of birth FE	Yes	Yes	Yes	Yes
Country-Year of birth FE	Yes	Yes	Yes	Yes
Observations	191,902	423,203	191,902	423,203
Mean of dep. var.	82.20	79.66	82.20	79.66

* Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Notes: Robust standard errors clustered at the district level are in parentheses. The dependent variable (low education) is an indicator that equals one if the mother has at most primary education and zero otherwise. The value is multiplied by 100, so the coefficients represent percentage point changes. The table shows the coefficient of an indicator that is equal to one if a child was exposed to a heat wave shock at conception (during months 2-9 of pregnancy) and zero otherwise. Control variables include indicators for Christian religion and urban residence, maternal current age, age at childbearing, and child birth order. The mean of the dependent variable is calculated at the baseline (i.e., HWMId = 0).