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Temperature and risk of diarrhoea among children in Sub-Saharan Africa

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ABSTRACT

We assess the effects of temperature on the risk of diarrhoea, one of the leading causes of mortality and morbidity among children under 5. Our analysis focuses on Sub-Saharan Africa, the continent where temperatures have been rising at twice the global rate and diarrhoea prevalence rates are highest. Drawing on child-level survey data and exploiting quasi-random variation in temperature realisations around the date of interview, we show that temperature strongly influences diarrhoea incidence as well as prevalence of wasting (low weight-for-height ratios). Using binned regressions, we document that the effects are particularly strong in the temperature range 30–37.5 °C. We further find that access to improved sanitation and drinking water facilities mitigates these temperature-induces risks. This implies that building up such capacities is a particularly pressing issue in regions that will experience strong increases in temperatures and lack adequate access to sanitation and safe water. We use our estimates together with climate projections to identify these areas.

1. Introduction

Each year, more than a billion episodes of diarrhoea occur among children under 5 (Troeger, Blacker, & Khalil, 2018). Of these, around half a million result in death, making diarrhoeal diseases a leading cause of child mortality. Further increasing the health burden is the fact that diarrhoeal episodes can impair growth and other health-related outcomes, such as wasting (Khalil, Troeger, & Rao, 2018). Temperature can influence the intensity of transmission in a variety of ways. For example, higher temperatures increase survival probabilities and reproduction rates of bacteria, the most important group of organisms causing diarrhoeal episodes (Carlton, Woster, DeWitt, Goldstein, & Levy, 2016; Levy, Woster, Goldstein, & Carlton, 2016; Troeger, Khalil, & Blacker, 2020). Warmer temperatures can also provide a more hospitable environment for agents—particularly flies—that spread the germs (Wu, Yongmei, Zhou, Chen, & Bing, 2016) and thus increase infection probabilities. These mechanisms imply that a rise in temperatures increases the prevalence of diarrhoeal diseases (Carlton et al., 2016). In the light of global warming, this makes identifying and quantifying the effects of temperature on the risk of diarrhoea and diarrhoea-induced health effects an important issue.

Despite the epidemiological literature documenting a positive relationship between temperature and diarrhoea (e.g., Carlton et al. (2016)), causal evidence on how this relationship plays out at the aggregate level, i.e., in general equilibrium, is so far lacking. To identify causal effects we (a) build on a spatially and temporarily comprehensive dataset on diarrhoeal episodes and temperature conditions, and (b) develop an identification strategy that allows us to circumvent issues related to omitted variables and selection biases. Our first contribution is to provide empirically rigorous, large-scale, evidence for the existence of a causal effect of temperature on diarrhoea risk in Sub-Saharan Africa. Our second main contribution is to document that water and sanitation infrastructure can substantially mitigate the adverse effects of temperature on child health. This implies that building up corresponding infrastructure is an important adaptation mechanism to global warming.

Our study draws on individual-level data from the Demographic and Health Surveys (DHS). In total, we observe 596,522 children under 5. Information on their health status was collected in 80 survey waves which together cover 30 Sub-Saharan African countries and the time period 1991–2017. To each individual, we match short-run temperature conditions, defined as the average temperature at the location of residence over the two-week period leading up to the interview. We then analyse how variation in this variable

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influences the prevalence of diarrhoea. Throughout, we control for local long-run (10-year average) temperature conditions that usually prevail in the two-week pre-interview window. This accounts for the possibility that the general temperature environment influences local prevalence of diarrhoea via indirect channels (e.g., through adaptation processes). Conditioning on long-run average temperatures furthermore accounts for the possibility that survey implementation schedules are influenced by expectations about local weather conditions. Our empirical approach thus exploits the quasi-random nature of temperature realisations around the day of the interview, conditional on local expected temperatures. This means that we compare diarrhoea prevalence among children surveyed in regions that experience positive deviation from local average temperatures with individuals residing in areas where temperatures are below expected interview-period-specific values. For identification we require that the timing of the interviews is orthogonal to the temperature realisations around the survey date, conditional on the local expected temperature during this period. In an array of validation and robustness checks we provide evidence for the plausibility of this assumption. For example, we show that our estimates remain stable when we account for a wide variety of individual, household, locational and time-varying characteristics. Furthermore, we perform falsification tests by shifting the interview date one year into the past and future, respectively. In both cases, average temperatures during the two-week window leading up to the placebo dates are unrelated to the risk of diarrhoea. To mitigate concerns related to the possibility that survey-elicited information on diarrhoeal episodes may be unreliable, we validate our results using low weight-for-height ratios (i.e., wasting) as an alternative outcome variable. Consistent with severe diarrhoea, we find that increased temperatures raise the risk of wasting.

Our regression results document that temperature is an important risk factor for diarrhoea. A one-standard deviation increase in temperature—equal to rise of 4.5 °C—during the 2 weeks prior to the interview raises the probability of diarrhoeal episodes by 1.2 percentage points.[1] Evaluated at the baseline risk of 15%, this amounts to an increase of almost 8%. We investigate the existence of non-linearities by estimating the effect across different temperature bins. We find that effects are particularly pronounced at temperatures between 27 and 37°C.

Consistent with the faecal-to-oral contact being the main transmission pathway, we find that improved sanitation—particularly access to flush toilets—plays an important role in mitigating the temperature-induced effect. For children residing in households with flush toilets, the diarrhoea risk caused by temperature shocks drops by 75%. Access to improved drinking water facilities also has an attenuating effect, although to a lesser extent. We additionally find evidence of substantial positive spillover effects. The temperature-induced diarrhoea risk is dramatically reduced when a high proportion of neighbours has access to improved sanitation and drinking water facilities. For example, moving from a neighbourhood in which no one has access to flush toilets to one with a 100% penetration rate reduces the temperature-induced diarrhoea risk by 85%. The existence of such strong herd protection effects implies that interventions that ensure access to safe water and sanitation are crucial in mitigating and adapting to the climate-change-induced risk of diarrhoea.

Together, our results show that increasing temperatures make improving sanitation and drinking water—thereby interrupting pathogen transmission pathways—an even more pressing issue in the context of rising temperatures. In the final step of our analysis, we use our estimates combined with temperature projections from climate models to map expected changes in diarrhoea prevalence. Taking existing differences in access to safe water and sanitation into account, we find that Central African regions are projected to experience the greatest temperature-induced risk of diarrhoeal episodes. These results are to be interpreted with caution, however, as they abstract from any potential adaptation processes (such as future infrastructure investments).

Our study contributes to the understanding of spatial and temporal variation in the prevalence of diarrhoeal diseases and wasting. Most directly, we add to the literature that investigates the effects of temperature on the risk of diarrhoea. Existing evidence primarily stems from case studies (see Carlton et al. (2016) for a systematic review). Overwhelmingly, the results suggest a positive relationship between temperature and diarrhoea incidence. By nature, however, case studies are limited in their geographical and temporal scope, curtailing the generalisability of findings. Furthermore, disentangling causation from correlation is typically not possible. This is also the case for studies conducted at the country or regional level (e.g., Bandyopadhyay, Kanji, & Wang, 2012; Carlton et al., 2016). The existence of many potentially confounding factors—such as demographic, economic or institutional differences—make identification and quantification of temperature effects very challenging.[2] Our study addresses these issues by combining nationally representative individual-level data which cover a long time period and the majority of Sub-Saharan African countries with spatially and temporally highly disaggregated information on temperature conditions.[3]

More broadly, our paper relates to the identification of climatic factors that influence child health. Weather shocks during early life stages have been shown to influence child mortality and morbidity directly (e.g. Burgess, Deschenes, Donaldson, & Greenstone, 2017; Isen, Rossin-Slater, & Walker, 2017; Flückiger et al., 2018). Furthermore, there is mounting evidence that such shocks can have long-term effects on health and labour market outcomes (e.g. Baird, Friedman, & Schady, 2011; Shah et al., 2017).

Our results also directly speak to the research that highlights access to improved sanitation and drinking water facilities as crucial factors in the prevention of diarrhoeal diseases (see e.g., Fewtrell et al. (2005),Majorin, Torondel, Chan, & Clasen (2014), or Freeman, Garn, & Sclar (2017) for a review of studies). Our findings suggest that this becomes even more critical in the context of rising temperatures. By using temperatures projections and investigating their implications for the prevalence of diarrhoea across Sub-Saharan Africa, we also contribute to the very active research area on the effects of climate change on health and socio-economic development (e.g., Patz, Campbell-Lendrum, Holloway, & Foley, 2005; Burke, Hsiang, & Miguel, 2015; Costinot, Donaldson, & Smith, 2016).

The remainder of this paper is structured as follows: In the next section we outline our empirical strategy. The data to which it is applied to is then presented in Section 3. We discuss our regression results in Section 4 and use these in combination with temperature projections to map changes in diarrhoea risk within Sub-Saharan Africa in Section 5. Finally, Section 6 concludes.

[1] To put this into context: Almazroui et al. (2020) compare 27 global climate models from the sixth phase of the Coupled Model Intercomparison Project. They find that the median temperature is projected to be 1.39 to 4.36°C higher during the period 2070–2099 relative to the reference period 1981–2010.

[2] Furthermore, information contained in regional-level temperature data can be very noisy due to the need for aggregation over time and space.

[3] The use of the DHS data also addresses the concern that the hitherto emerged picture of a positive relationship between ambient temperature and diarrhoea risk could be the result of publication bias [p. 126] (Carlton et al., 2016).

2. Empirical strategy

The basis of our empirical analysis is a linear probability model in which we account for an extensive set of fixed effects (Kolstad & Moore, 2020). When we investigate the existence of heterogeneities across different temperature ranges in Section 4.2, we additionally introduce a binned (flexible) regression model.

Our main OLS regression model can be represented as:

$$o_{i,k,c,dmy} = \beta T_{k,c,dmy} + \gamma \overline{HT}_{k,c,dmy} + \gamma\prime \mathbf{X}_{i,k,c,dmy} + \sigma_{c,my} + \lambda\prime \Lambda_{i,k,c,dmy} + \varepsilon_{i,k,c,dmy} \quad (1)$$

where i denotes the child, k the DHS cluster (i.e. the location) in which the individual resides, c the country, and dmy the date (day, month, and year) of the interview. The main regressor of interest, $T_{k,c,dmy}$, represents the average local temperature during the two-week period leading up to the interview.[4] To estimate its effects on child health outcomes $o_{i,k,c,dmy}$, we exploit the quasi-random nature of temperature realisations relative to the timing of the DHS interviews. The crucial assumption underlying our empirical approach is that these temperature realisations are unrelated to the timing of the survey as well as (correlated) factors that influence health outcomes.

A major concern is that $T_{k,c,dmy}$ is correlated with other local geographic characteristics (e.g., altitude, rainfall or proximity to coast). These characteristics could, for example, have an effect on child health by influencing the level of development, structure of the local economy, quality of institutions, or more general biological and behavioural adaptation processes (e.g., Acemoglu, Johnson, & Robinson, 2001; Dell, Jones, & Olken, 2014; Henderson, Storeygard, & Deichmann, 2017). To ensure that we isolate short-run temperature effects, we control for historical temperature realisations $\overline{HT}_{k,c,dmy}$ throughout. This variable is defined as the average temperature over the same set of days that fall into the two-week pre-interview window, but computed for the 10 years preceding the survey (rather than for the actual interview year).[5] The inclusion of historical—i.e., expected—temperature averages also mitigates concerns related to the possibility that the design and implementation of DHS surveys is influenced by seasonal weather patterns (e.g., Wright, Yang, & Walker, 2012). Conditioning on past values thus implies that the coefficient of interest β captures the direct effects of recent temperature realisations on health outcome *conditional* on usually prevailing temperature conditions. That is, we compare diarrhoea incidence of children that live in regions that are warmer than usual with individuals surveyed in areas where temperatures are below expected interview-period-specific values.

In all regression, we control for an array of child characteristics $\mathbf{X}$. In the most parsimonious version, the controls include fixed effects for gender, age, and birth order. Further included are climate-zone $\times$ country $\times$ month-of-year-of-interview fixed effects ($\sigma_{c,my}$) which absorb any region-specific variation within a given month. The inclusion of these dummies addresses the concern that variation in temperatures may be correlated with other seasonally-driven morbidity shocks that affect regions differently depending on their local climate.[6] To further assuage worries related to omitted variables, we successively extend our setup to include a growing variety of household, geographic and climatic characteristics ($\Lambda_{i,k,c,dmy}$). The idiosyncratic error term is represented by $\varepsilon_{i,k,s,dmy}$ and standard errors are clustered at the DHS cluster level. Finally, all observations are weighted using the sample weights available from the DHS.[7]

3. Data

Information on health status along with other individual and household-level characteristics are taken from the Demographic and Health Surveys (DHS). Our analysis is restricted to children under 5 and to survey waves that include geocoded information on the location of residence (DHS clusters). With these restrictions, our final dataset consists of 596,522 observations gathered in 80 survey waves. These were conducted between 1991 and 2017 and cover 30 Sub-Saharan African countries.[8]

Our key outcome is an indicator variable that takes the value of one if a child is reported to have had diarrhoea in the two weeks prior to the interview.[9] We use wasting as a secondary outcome. This is a dummy variable indicating whether a child had a weight-for-height ratio that is below two standard deviations of the median WHO growth standards. Additionally, we extract information on a household's access to improved sanitation and drinking water facilities. The definition of these facilities, developed by the Joint Monitoring Program (JMP) for Water Supply and Sanitation of UNICEF and WHO, is very broad. Facilities classified as improved sanitation range from pit latrines with slabs to flush toilets that are connected to networked sewage systems. Similarly, the term 'improved drinking water sources' comprises water drawn from protected wells, boreholes, and piped taps.[10] The breadth of the JMP's definitions is likely to mask important differences in the diarrhoea-risk-reducing capabilities of the various types of facilities. We therefore create four mutually exclusive subgroups. Improved sanitation facilities are divided into two classes: (i) improved pit latrines and (ii) flush toilets. These two types differ structurally in that flush toilets pipe waste out of the household's plot (or community) for disposal. The category of improved drinking water sources is also split into two subtypes: (iii) piped water (into dwelling or plot) and (iv) protected boreholes, (public) standpipes, wells, and springs. For brevity, the latter class is subsequently referred to as 'protected groundwater'. On the basis of these four subgroups, we then construct dummy variables that capture whether a household has access to the respective facility. Similarly, we compute the share of neighbours, defined as other households residing within the same DHS cluster, that have access to the four types of improved sanitation and water.Based on the geocoded location of residence, we link the survey data to information on local weather conditions. These are extracted from the CPC Global Temperature database which is provided by the NOAA/OAR/ESRL Physical Sciences Division (CPC).[11] For the period 1979–2019, the CPC reports daily temperatures (and other weather variables) at a spatial resolution of 0.5 $\times$ 0.5 degrees. We use this information to construct our main explanatory variable, defined as the average temperature over the two weeks running up to (and including) the day of interview. Similarly, we compute the histor-

[4] The two-week window is chosen to match the phrasing of questions in the DHS survey (see Section 3).

[5] Our results are robust to changing the time window considered in the computation of long-run averages (see Section 4).

[6] In robustness checks, we show that we obtain very similar results if we use less restrictive fixed effects.

[7] We obtain very similar results if we do not use weights (see Table B.3).

[8] Table A.1 lists the included survey waves. The geographical scope of our analysis, along with the location of DHS clusters, is depicted in Fig. A.1.

[9] This information is elicited from the child's caregiver, usually the mother. The precise wording of the questions is: "Has (NAME) had diarrhea in the last 2 weeks?"

[10] See Table A.3 for a full list of facility types that are classified as either improved sanitation or improved drinking water.

[11] https://www.esrl.noaa.gov/psd/

Table 1
Descriptive Statistics key variables.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
			Child		
Diarrhoea	0.151	0.358	0	1	596,522
Age child	2.879	1.414	1	5	596,522
Gender child (male)	0.503	0.500	0	1	596,522
Birth order child	1.323	0.540	1	6	596,522
			Sanitation and Drinking Water		
Flush toilet HH	0.081	0.272	0	1	596,522
Improved pit latrine HH	0.250	0.433	0	1	596,522
Piped water HH	0.130	0.337	0	1	596,522
Groundwater HH	0.277	0.448	0	1	596,522
			Temperature		
Temperatures 15-day window (raw)	24.859	4.509	6.050	37.856	596,522
Temperatures 15-day window (SD)	0	1	−4.170	2.882	596,522

ical temperature average across the same set of 15 days in the 10 years prior to the year in which the interview took place.[12],[13]

In the regression analysis, we also control for an increasingly wide variety of household and locational characteristics. These variables are described as they become relevant; their sources are listed in Table A.2.

Table 1 reports summary statistics of the key variables. Almost one in six children had experienced diarrhoea in the two weeks leading up to the interview, confirming that diarrhoeal diseases constitute a major health burden in Sub-Saharan Africa. The data also clearly show that levels of sanitation infrastructure are low. Only 33 percent of households in our sample have access to improved means of disposing of faeces (i.e., either flush or improved pit toilets), while 41 percent draw their drinking water from sources that are classified as safe. Starting with the next section, we will assess whether above-normal temperatures increase the number of diarrhoeal episodes. As mentioned above, the critical identifying assumption underlying our empirical approach is that temperature realisations around the date of interview are unrelated to other factors that influence health outcomes, conditional on usually prevailing temperatures. As a first step in assessing the validity of this assumption, we conduct a balance test for several child, household, and locational characteristics that could correlate with the timing of the interview and our outcome. Table 2 presents two variants of the balance test: In column (1) we do not control for past temperature conditions whereas these are accounted for in column (2).[14],[15] In the first case, the majority of outcomes are statistically significantly related to the temperature realisations in the two weeks leading up to the interview. However, once average temperature conditions are taken into account, this is only true for the association with gender. While we always account for the sex of a child in our regressions, this may still raise the suspicion that our subsequent results are primarily driven by males. In Tables B.1, B.2, we show that this is not the case; effects are similar for both genders.

Overall, Table 2 illustrates that accounting for general (long-run) temperature conditions is important in order to isolate effects that are driven by differences in temperatures during the days preceding interviews. Consequently, we control for the general temperature environment in all our regressions

4. Main results

4.1. Temperature and diarrhoea risk

In Table 3 we test if an increase in temperature influences the prevalence of diarrhoea. We start by regressing the indicator for diarrhoea within the past 15 days on average temperature during the same pre-interview period conditional on a parsimonious set of controls. In addition to the historical temperature conditions, this set includes dummies for a child's gender, age and birth order, an indicator variable for breastfeeding, as well as country $\times$ climate-zone $\times$ year $\times$ month fixed effects. As discussed above, the latter account for local weather, political or economic shocks that could potentially influence child health. The result, presented in column (1), documents that higher temperatures elevate the risk of diarrhoea. The magnitude of the effect is substantial. A one-standard deviation rise in temperature—equal to a rise of 4.5°C—raises the likelihood of diarrhoeal episodes by 1.6 percentage points. Evaluated at the sample mean of 15%, this corresponds to a 11% increase in risk.

In column (2), we add controls for mother- and household-level characteristics. These encompass fixed effects for the mother's age, marital status and educational attainment. The household-level controls are: a wealth index and separate indicator variables for access to the four subgroups of improved sanitation and drinking water facilities. Compared to column (1), the temperature coefficient remains very stable. This is also the case, when we account for a variety of time-invariant and time-varying locational aspects that could influence the prevalence of diarrhoea in column (3). These DHS-cluster-level controls include climatic aspects (historical and recent precipitation[16], agricultural suitability, (absolute) latitude, longitude, and elevation).[17] We also control for whether a location is classified as being urban as well as the share of house-

[12] The 10-year lag is chosen as to maximise the number of surveys that can be included in our analysis. As mentioned above, the first DHS survey for which geocoded information on the respondents' residence is available was conducted in 1991.

[13] Formally, the pre-interview conditions in the year of survey are defined as:

$$T_{k,c,dmy} = \frac{1}{15}\sum_{s=0}^{S=14} \mathrm{t}_{k,c,dmy-s},$$

where k represents the DHS cluster an individual lives in, c the country, and dmy is date of interview. Mean temperature on a given day dmy is symbolised by $\mathrm{t}_{k,c,dmy}$. Similarly, historical temperature averages over the same two-week window in the ten preceding years ($y-10, y-9, \dots, y-1$) are given by:

$$\overline{HT}_{k,c,dmy} = \frac{1}{10}\sum_{y=-10}^{Y=-1} \frac{1}{15}\left(\sum_{s=0}^{S=14} \mathrm{t}_{k,c,dmy-y-s}\right).$$

[14] In both cases, we condition on climate-zone $\times$ country $\times$ month-of-year of interview fixed effects to ensure that we compare individuals that reside in the same country and are surveyed around the same time.

[15] All variables are standardised to a mean of zero and a standard deviation of one to facilitate comparison of coefficients.

[16] The precipitation measure is constructed in analogy to the temperature measures (see Section 3.)

[17] Data sources listed in Table A.2.

Table 2
Balance test: Regressing characteristics on temperature conditions around the time of interview.

Dependent Variable:	Not Controlling for Long-Run Temperature Conditions (1)	Controlling for Long-Run Temperature Conditions (2)
Age child (SD)	−0.002	0.009
	(0.004)	(0.008)
Gender child (SD)	0.008	0.021**
	(0.005)	(0.010)
Birth order (SD)	−0.011**	−0.005
	(0.005)	(0.009)
Breastfed (SD)	0.010**	0.001
	(0.005)	(0.009)
Age mother (SD)	−0.036***	−0.013
	(0.006)	(0.013)
Wealth index HH (SD)	−0.063***	0.017
	(0.017)	(0.032)
Flush toilet HH (SD)	−0.029*	−0.006
	(0.016)	(0.026)
Improved pit latrine HH (SD)	−0.029**	0.022
	(0.012)	(0.024)
Piped water HH (SD)	−0.043***	0.011
	(0.016)	(0.028)
Groundwater HH (SD)	−0.015	0.021
	(0.013)	(0.026)
Share flush toilet HH (SD)	−0.034*	−0.010
	(0.021)	(0.033)
Share improved pit latrine HH (SD)	−0.045***	0.027
	(0.017)	(0.033)
Share piped water HH (SD)	−0.034*	−0.010
	(0.021)	(0.033)
Share groundwater HH (SD)	−0.021	0.030
	(0.019)	(0.036)
Urban residence (SD)	−0.020	0.048
	(0.021)	(0.038)
Controls historical temperatures	No	Yes
Country × climate zone × year × month FE	Yes	Yes
Observations	596,522	596,522

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview. Every cell represents the outcome of a separate regression in which the respective variable is regressed on the average temperature during the 15 days preceding the interview as well as country × climate-zone × year × month fixed effects. In column (2), we additionally control for historical temperature conditions. All variables are standardised to a mean of zero and standard deviation of one.

holds within a cluster that have access to improved sanitation and drinking water facilities.

The coefficient stability across varying setups provides a first indication that our measure specifically captures variation in temperatures during the weeks before the interview. To further substantiate this notion, we conduct two falsification tests by replacing average temperature over the 15-day period leading up to the interview with average temperature conditions during the same two-week window in the year preceding (column (4)) and following (column (5)) the survey. In both cases, the coefficient of the time-inconsistent temperature measure is not statistically significant and close to zero.

In Appendix B, Table B.3, we conduct a battery of robustness tests to further document the stability and validity of our results. Specifically, we show that our estimates remain stable if we control for additional locational characteristics or include local malaria suitability indices. We further show that we obtain qualitatively equivalent results if we vary the time span used in the computation of long-run average temperature conditions, cluster standard errors by administrative regions, or run regressions without weighting observations. As mentioned in Section 3, we also show that results are very similar if we conduct our analysis separately by gender (Tables B.1,B.2). Finally, we show that our results do not depend on the inclusion of the demanding country × climate zone × year × month fixed effects. Table B.4 illustrates that estimates are very close to the ones produced by our preferred specification when we account for less restrictive sets of dummies (e.g., country and month fixed effects or country × month fixed effects).

To address worries that self-reported data on diarrhoeal episodes may be unreliable (Schmidt et al., 2010), we validate our findings using wasting as an alternative proxy. This objective measure takes a value of one if a child's weight-for-height ratio is below two standard deviations of the median WHO growth standards. Consistent with diarrhoea leading to weight loss in the short run, we document that a rise in temperature augments the risk of wasting (Table B.3, column (6)). On the other hand, we do not find any effect on height of children (Table B.3, column (7)). This provides further evidence for the validity of our analysis as (temperature-induced) diarrhoeal episodes cannot influence height in the short run.

Before looking at the effectiveness of different interventions in mitigating temperature-driven risks of diarrhoea, we look at the dynamics of the effect over time and temperature ranges. Our analysis of temporal dynamics focusses on the four-month window around the interview. In a first step, we divide this period into 8 separate two-week bins and compute the average temperature for each of these bins. In a second step, we use regression Eq. (1) in our preferred specification (column (3) of Table 3) to estimate their effects on the risk of diarrhoea. Fig. 1 visualises the results. Only temperature conditions in the two weeks immediately preceding the interview statistically significantly influence diarrhoea prevalence rates.[18] The size of the point estimate (0.016) is very similar to the one presented in column (3) of Table 3. Coefficients of the remaining two-week bins are close to zero and not statistically significant at conventional confidence level. The null results of post-interview temperature realisations is reassuring and provides further evidence that our estimates specifically capture differences in local temperatures during weeks preceding interviews. The non-significant effects of temperature conditions during the 3 to 8 weeks leading up to the interview, on the other hand, indicate that the time lag between temperature shocks and response is very short. This is consistent with diarrhoea case numbers responding quickly to changes in environmental conditions as well as the fact that most types of diarrhoeal diseases last for less than two weeks (Lamberti et al., 2012; Carlton et al., 2016).

4.2. Non linearities

The estimates discussed so far show that above-normal temperatures increase the risk of diarrhoea. However, these findings represent average effects and could mask potentially existing heterogeneities in the effect across different temperature ranges. To assess whether effects vary over the temperature distribution, we follow the recent literature by creating temperature bins of 2.5°C and counting the number of days that fall into the respective bin during the two-week pre-interview period. Specifically, we create the following bins: $(-\infty, 10), [10, 12.5), \ldots\ [35, 37.5)$, and $[37.5, \infty)$. We choose the $[12.5, 15)$ bin as reference group and run the following flexible model:

[18] The point estimate of the temperature conditions in the two weeks immediately preceding the interview is statistically significantly larger than the other coefficients at a confidence level of at least 90 percent.

Table 3
Temperature and Diarrhoea.

	Diarrhoea during last 15 days				
	(1)	(2)	(3)	(4)	(5)
Temperatures 15-day window current year (SD)	0.016*** (0.005)	0.016*** (0.004)	0.014*** (0.004)		
Temperatures 15-day window past year (SD)				0.005 (0.004)	
Temperatures 15-day window next year (SD)					0.004 (0.004)
Controls child	Yes	Yes	Yes	Yes	Yes
Controls mother	No	Yes	Yes	Yes	Yes
Controls household	No	Yes	Yes	Yes	Yes
Controls location	No	No	Yes	Yes	Yes
Controls historical temperatures	Yes	Yes	Yes	Yes	Yes
Country × climate zone × year × month FE	Yes	Yes	Yes	Yes	Yes
Observations	596,522	596,522	596,522	596,522	596,522
R-squared	0.078	0.080	0.081	0.081	0.081

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

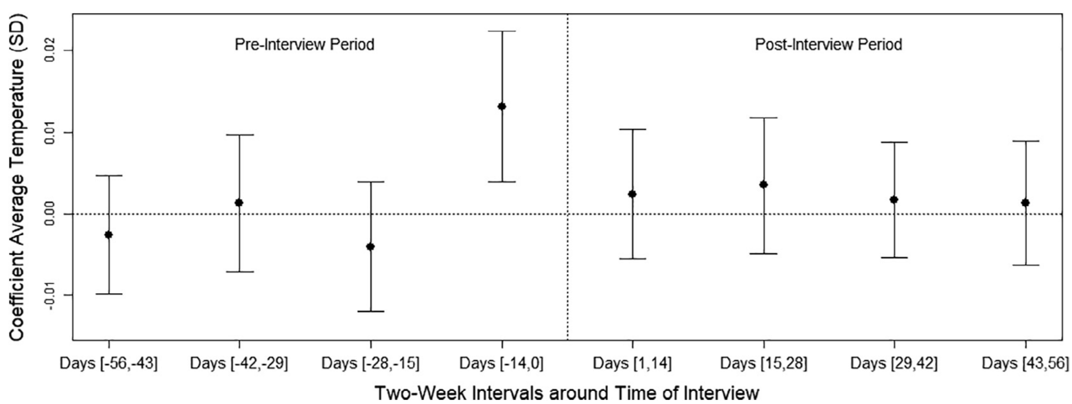

Fig. 1. Figure depicts the point estimates and 95% confidence intervals of the effects of average temperatures during the respective 2-week bin.

$$o_{i,k,c,dmy} = \sum_b \beta^b T^b_{k,c,dmy} + \sum_b \gamma^b \overline{HT}^b_{k,c,dmy} + \gamma\prime \mathbf{X}_{i,k,c,dmy} + \sigma_{c,my} + \lambda\prime \Lambda_{i,k,c,dmy} + \varepsilon_{i,k,c,dmy} \quad (2)$$

where the variable $T^b_{k,c,dmy}$ represents the number of days in the two-week pre-interview period that fall into the temperature range bin b. β^b captures the effect relative to the bin $[12.5, 15)$. Again we control for the local long-run temperature regime, $\overline{HT}^b_{k,c,dmy}$. For each temperature bin, we compute the average over the same two-weeks window in the preceding 10 years. All other variables are defined as described in Section 2. Fig. 2 depicts the point estimates resulting from running regression Eq. (2). Relative to the reference bin of $[12.5, 15)$, we observe a hump shape in the relationship between temperature and diarrhoea at the upper end of the temperature distribution. The finding is in line with results from epidemiological studies that analyse optimal temperature ranges for bacteria-induced diarrhoea. For example, optimal temperature for development is around 37 °C for two main types of bacteria that trigger diarrhoeal episodes, *Shigella* and *Escherichia coli.*[19] At low and very high temperatures bacterial (and vector) development is hampered.

The results presented in Fig. 2 illustrate that the temperature-induced risk of diarrhoea substantially varies across its distribution. For the remainder of the paper, however, we revert to the parsimonious setup introduced in Eq. 1. Two main reasons motivate this choice: Firstly, we will be analysing the mitigating effects of water and sanitation infrastructure in the next section. This would be difficult within a regression framework that uses temperature bins. Secondly, we will combine our estimates with temperature projections to understand how future temperature changes affect the risk of diarrhoea across Sub-Saharan Africa in the final Section of the paper (5). The temperature projections, however, are not available at a sufficiently granular (i.e. daily) level to be combined with the results produced by the binned regression.

4.3. Temperatures, diarrhoea, sanitation and water

The results presented above document that the incidence of diarrhoea among children under 5 is increasing in temperature. As mentioned previously, the vast majority of diarrhoeal episodes are caused by faeco-oral transmission of pathogens. Important pathways include direct contact with faeces (i.e., touching), ingestion of contaminated water or food, and infection via flies that have come into contact with faecal matter (e.g., Wagner & Lanoix, 1958; Byers & Guerrant, 2008). Temperature can influence the intensity of transmission in a variety of ways. For example, higher temperatures increase survival probabilities and reproduction rates of bacteria, the most important group of organisms responsible for diarrhoeal episodes (Carlton et al., 2016; Levy et al., 2016; Troeger et al., 2020). Furthermore, warmer temperatures can provide a more hospitable environment for agents—particularly

[19] See for examplehttps://food.unl.edu/escherichinia-coli-o157h7-e-coli andhttps://food.unl.edu/shigella

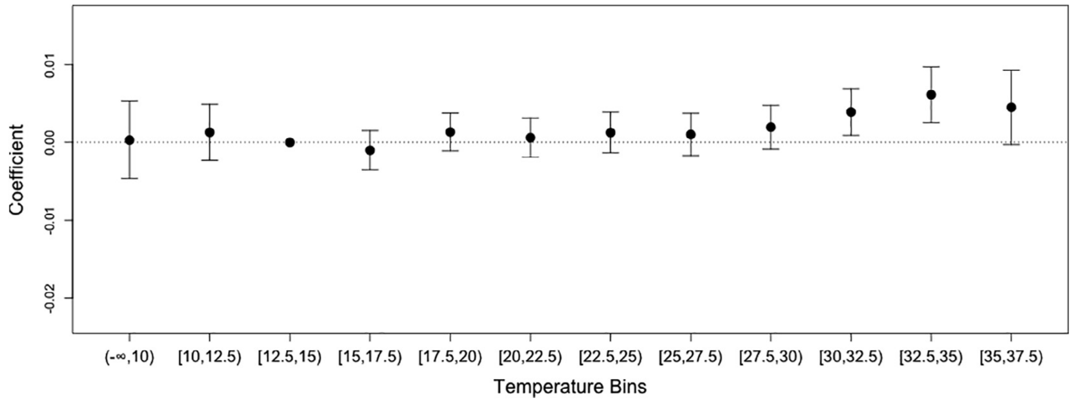

Fig. 2. Figure depicts the point estimates and 95% confidence intervals of the effects of $(-\infty, 10)$, $[10, 12.5)$, ... $[35, 37.5)$, and $[37.5, \infty)$. The reference bin is $[15, 17.5)$. Standard errors are clustered at DHS cluster level. Controls include fixed effects for child's gender, age and birth order, an indicator variable for breastfeeding, as well as country $\times$ climate-zone $\times$ year $\times$ month fixed effects.

flies—that spread the germs (Wu et al., 2016) and thus increase infection probabilities.[20] Below, we analyse the relative importance of different barriers and interventions in mitigating these temperature-induced risks. To empirically assess their effectiveness, we revert to using regression Eq. (1) and creating interaction terms between temperature and the various types of barriers.

In column (1) of Table 4 we start by analysing the mitigating effects of breastfeeding. Breastfed children are naturally protected against pathogen transmission via contaminated water and food (Jayachandran & Kuziemko, 2011; Lamberti, Fischer, Walker, Victora, & Black, 2011). If this pathway is important, we should see substantial protective effects. This is, in fact, what we observe. The interaction term between breastfeeding and temperature is highly statistically significant and negative. The point estimate implies that a one-standard deviation increase in temperature is 68% less likely to trigger diarrhoeal episodes if a child is breastfed. Due to the strong association between age and breastfeeding, this result also implies that the temperature-related diarrhoea burden primarily falls onto non-infant children.[21] Mitigating risks for this group of children thus requires alternative interventions.

Inadequate water, sanitation and hygiene is a catalyst for the spread of faeco-oral diseases and estimated to be responsible for the majority of the diarrhoea-related deaths worldwide (World Health Organization, 2014). A natural conjecture therefore is that exposure to temperature-induced risk of diarrhoea depends on the availability of safe sanitation and water. We start testing this conjecture by investigating whether access to improved sanitation—measured by the presence of pit latrines and flush toilets—reduces diarrhoea incidence that results from a surge in temperatures.[22,23] Column (2) of Table 4 unveils stark differences in the degree to which the two types of sanitation facilities mitigate temperature-driven risks. Compared to children without access to improved sanitation, diarrhoea incidence remains unchanged in households with (improved) pit latrines. On the other hand, the likelihood of diarrhoeal episodes resulting from surges in temperatures is substantially reduced in households with flush toilets. For children residing in these households, a one-standard deviation increase in temperature raises diarrhoea incidence by 5 percentage points. This represents a 64% reduction in prevalence relative to children in households without sanitary means of disposing of excreta. A potential explanation for this differential picture is that flush toilets reduce the risk of direct and indirect contact with faeces by piping waste out of the household's plot (or community) for disposal (Ferrer et al., 2008; Waddington, Snilstveit, White, & Fewtrell, 2009; Norman, Pedley, & Takkouche, 2010; Capuno, Tan, & Fabella, 2015). With pit latrines, the risk of indirect exposure (e.g., via flies or groundwater), still exists.

We next compare children with and without access to improved drinking water sources. As described in Section 3, improved sources are divided into two sub-groups: piped water and (protected) groundwater. Column (3) shows that only the interaction between temperature and groundwater is statistically significant at conventional confidence levels. However, the coefficient is of modest size. One possible explanation for the limited size and significance of the water effects is that even if the sourced water is safe, inadequate storage may lead to contamination with pathogens, for example through contaminated drinking cups, hands, or storage containers (Julian, 2016). Another possibility is that even if sources are classified as safe, they may actually be contaminated. A third possible explanation is that (drinking-water) interventions at the household level have—in isolation—only a limited impact potential. More effective are community-wide approaches, not least because they generate positive externalities (see Clasen et al. (2015) for a review).

To investigate the existence of externalities in the context of rising temperatures, we create interactions between temperature and the share of neighbouring households that have access to improved sanitation and drinking water. Column (4) reveals that there are, in fact, substantial positive spillovers in sanitation. Moving from a neighbourhood in which no one has access to flush toilets to one with a 100% penetration rate reduces the temperature-induced diarrhoea risk by 73%. The positive externalities can arise from several sources. For example, the direct reduction in diarrhoea incidence observed in households with flush toilets (column (2)) also implies that children living in these households are less likely to spread diarrhoeal diseases to neighbouring children. Furthermore, by piping water out of the community, the risk of contaminating groundwater is reduced. Neither of these channels are active in the case of (improved) pit latrines. This may explain why we do not observe any positive spillovers for this type of excreta disposal.

Externalities are also present when looking at water sources. Residing in areas with a high proportion of households that draw

[20] More generally, warmer weather can increase the risk of coming into contact with infectious organisms by altering human behaviour (e.g., need for more frequent rehydration (Carlton et al., 2016)). Furthermore, higher temperatures can weaken the immune responsiveness of humans, thereby making them susceptible to infections (Moriyama et al., 2019).

[21] In Table C.1 we formally show that this is the case by estimating separate temperature slope coefficients for the individual age groups ($[0, 1)$, $[1, 2)$, $[2, 3)$, $[3, 4)$, and $[4, 5)$.). The results document that a rise in temperature increases the risk of diarrhoea only for children aged 3 and older.

[22] See Section 3 for more details on the categorisation of sanitation and drinking water facilities.

[23] Note that uninteracted effects of water and sanitation facilities have already been accounted for in previous regressions.

Table 4
Heterogeneities.

	Diarrhoea during last 15 days					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperatures 15-day window current year (SD)	0.019*** (0.004)	0.014*** (0.004)	0.015*** (0.005)	0.015*** (0.005)	0.017*** (0.005)	0.016*** (0.004)
Breastfeeding × Temperatures 15-day window current year (SD)	−0.013*** (0.001)					
Flush toilet HH × Temperatures 15-day window current year (SD)		−0.009*** (0.003)				
Improved pit latrine HH × Temperatures 15-day window current year (SD)		0.002 (0.002)				
Piped water HH × Temperatures 15-day window current year (SD)			−0.002 (0.002)			
Groundwater HH × Temperatures 15-day window current year (SD)			−0.003* (0.002)			
Neighbourhood's share flush toilet × Temperatures 15-day window current year (SD)				−0.011*** (0.003)		
Neighbourhood's share improved pit latrine × Temperatures 15-day window current year (SD)				0.000 (0.003)		
Neighbourhood's share piped water × Temperatures 15-day window current year (SD)					−0.006* (0.003)	
Neighbourhood's share groundwater × Temperatures 15-day window current year (SD)					−0.009*** (0.003)	
Urban residence × Temperatures 15-day window current year (SD)						−0.007*** (0.002)
Historical temperatures	Yes	Yes	Yes	Yes	Yes	Yes
Controls child	Yes	Yes	Yes	Yes	Yes	Yes
Controls mother	Yes	Yes	Yes	Yes	Yes	Yes
Controls household	Yes	Yes	Yes	Yes	Yes	Yes
Controls location	Yes	Yes	Yes	Yes	Yes	Yes
Country×climate zone×year×month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	596,522	596,522	596,522	596,522	596,522	596,522
R-squared	0.081	0.081	0.081	0.081	0.081	0.081

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

water from protected sources reduces the temperature-related diarrhoea risk by around 50% (column (5)). In the final column, we look at heterogeneities along the urban–rural dimension. Consistent with the findings of columns (2)–(5), we find that the likelihood of diarrhoeal episodes reacts more strongly to variation in temperature in rural areas, i.e., locations with lower levels of safe sanitation and drinking water infrastructure (column (6)).[24]

Together, the results of Table 4 add to the already existing evidence that sanitation provides substantial herd protection for neighbouring households (Barreto et al., 2007; Andrés, Briceño, Chase, & Echenique, 2017; Geruso et al., 2018). They also show that community-wide access to adequate sanitation and drinking water facilities is key in containing temperature-induced risks of diarrhoea and adaptation to climate change. This implies that building up such resources is an even more pressing issue in areas that will experience an increase in temperature and today have low levels of adequate sanitation and water infrastructure. In the last part of our analysis, we use our regression results combined with temperature projections, to identify such regions.

5. Projections

To map predicted future increases in the risk of temperature-induced diarrhoeal episodes, we require temperature projections. These are taken from the WorldClim database.[25] The projections are available as 20-year averages for the whole of Sub-Saharan Africa at a spatial resolution of approximately 10 × 10 kilometres and are based on the World Climate Research Programme's Coupled Model Intercomparison Project phase 6 (CMIP6). In total, we draw on temperature projections from 23 climate models. For the following analysis, we average the projections for the next twenty years (i.e., 2020–2040) over all available models.[26] Averaged across Sub-Saharan Africa, temperature is predicted to increase by 3.68°C. Combining the future climate projections with observed historical temperature averages—also provided by WorldClim—we can then compute the projected *change* in temperature for each grid cell.[27] More specifically, we can calculate the projected local change in average temperature between the periods 1970–2000 and 2020–2040.

Under the non-trivial assumption that our estimates can be extrapolated to the whole of Sub-Saharan Africa, we can multiply the projected temperature changes with our point estimate for the effect of temperature on diarrhoeal risk.[28] The result—representing the unmitigated effects of temperature on the risk of diarrhoea—is depicted in Panel (a) of Fig. 3. Averaged across the whole of Sub-Saharan Africa, the future rise in temperatures is predicted to elevate the risk of diarrhoeal diseases by 1.17 percentage points. Compared to the diarrhoea incidence observed in our survey data—15.1%—this represents a substantial increase in risk. The strongest (unmitigated) temperature-induced increase in the risk of diarrhoea

[24] The share of individuals living in households with access to improved sanitation (water) is 23% (83%) in urban areas and 2% (52%) in rural areas.
[25] https://www.worldclim.org/data/cmip6/cmip6climate.html
[26] Table A.4 lists the climate models included.
[27] The historical climate data represent averages over the period 1970–2000 and are drawn from the WorldClim climate data version 2.1 (released 2020 and available here:https://www.worldclim.org/data/worldclim21.html).
[28] That is, we re-run regression Eq. (1) with the full set of controls as presented in Table 3, column (3). The only difference is that we do not standardise the explanatory variables.

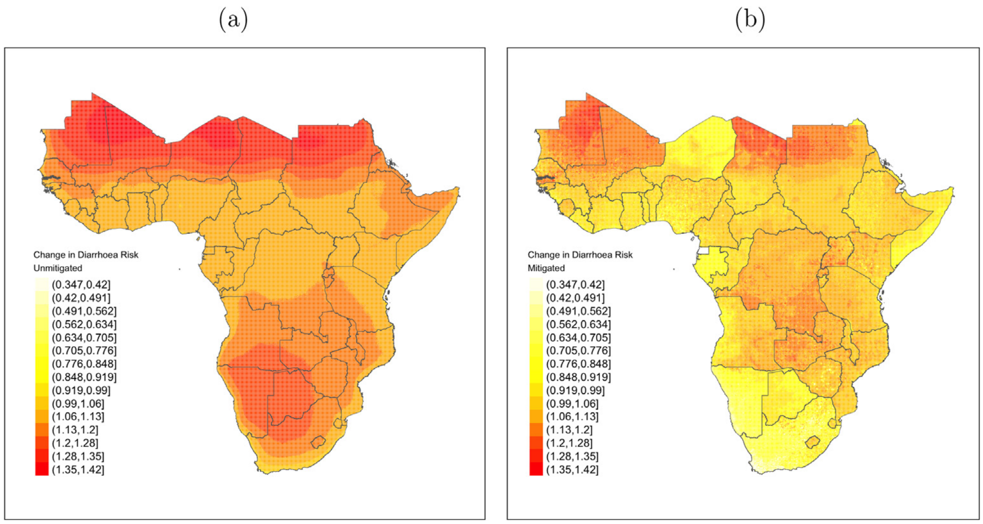

Fig. 3. Panel (a) depicts the unmitigated projected increase in temperature-induced risk of diarrhoeal episodes. Panel (b) shows the projections where current access to water and sanitation facilities are taken into account.

is projected for southwestern areas of Africa as well as the Sahel. It is important to note that these projections do not take into account any potential adaptation processes (such as changes in behaviour or investment in infrastructure). As documented in the previous section (Table 4), the temperature-related risk of diarrhoea is strongly mitigated by the availability of safe drinking water and sanitation facilities. When projecting temperature-induced changes in risk, it is therefore important to take into account the current access to safe water and sanitation. The corresponding data comes from Deshpande, Miller-Petrie, Lindstedt, Zuniga, and Hay (2020).[29] They use a wide variety of sources to estimate access to drinking water and sanitation facilities for the years 2000–2017. Crucially, these estimates are available at a very detailed spatial resolution for the whole of Sub-Saharan Africa and stratified according to the four water and sanitation sub-groups defined and used above: access to a flush toilet, improved pit latrine, piped water, and groundwater. For our analysis, we use the most recent year available (2017) and aggregate the data to the 10×10 kilometres level to make them congruent with the temperature projections. For each grid cell and subgroup of water and sanitation facility, we thus have an estimate for the proportion of households that have access to the respective type of facilities. We can then combine these shares with the temperature projections and the estimates obtained from the regression in which we include temperature as well as its interaction with the four types of water and sanitation facilities to generate the non-linear projected changes in the risk of diarrhoea.[30] The result is depicted in Panel (b) of Fig. 3. Compared to Panel (a), the average increase in temperature-induced risk of diarrhoea is slightly lower, now being at 1.02 percentage points. This relatively small reduction is due to the overall low levels of sanitation and water infrastructure. There are, however, marked differences in the spatial distribution of the risk, highlighting the importance of taking into account existing levels of access to safe water and sanitation when projecting temperature-related risk of diarrhoea. Access to safe water and sanitation is already (relatively) widespread in Southwestern Africa, implying that the temperature-associated increase in diarrhoeal risk is substantially mitigated. On the other hand, Central African regions—often characterised by poor access to water and sanitation facilities—are now projected to be among the regions most at risk. Subject to the caveat that these results represent (out of sample) predictions, our findings suggest that securing access to safe water and sanitation is particularly pressing in these regions.

6. Conclusion

This study shows that a rise in temperature increases the incidence of diarrhoea among children under 5 in Sub-Saharan Africa. Drawing on child-level survey data and exploiting quasi-random variation in temperature realisations around the date of interview, we show that temperature strongly influences diarrhoea incidence as well as prevalence of wasting (low weight-for-height ratios). The estimates of our preferred regression specification imply that a one-standard deviation increase in temperature—equal to rise of 4.5 °C—during the two weeks preceding the interview raises the probability of diarrhoeal episodes by 1.2 percentage points. Evaluated at the baseline risk of 15%, this amounts to an increase of almost 8%. Consistent with the faecal-to-oral contact being the main transmission pathway, we find that improved sanitation—particularly access to flush toilets—plays an important role in mitigating the temperature-induced effect. For children residing in households with flush toilets, the diarrhoea risk caused by temperature shocks drops by 75%. Using temperature projections for the next 20 years combined with our estimates and information on current levels of access to safe water and sanitation, we predict changes in diarrhoea risk induced by rises in temperature. The results indicate that Central African regions will see the greatest increase in the risk of diarrhoeal diseases. These are also areas typically characterised by poor access to safe water and sanitation. This implies that building up such capacities is a particularly pressing issue in regions that will experience strong increases in temperatures and today lack adequate access to sanitation and safe water.

A lot of research has gone into developing and implementing strategies to provide safe water and sanitation for all. One main insight has been that there is no one-size-fits-all solution [e.g.,]

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[29] We thank Benn Sartorius for sharing the data.

[30] For a given cell the projected change in risk of diarrhoeal episodes (Δd) is given by:

$$\Delta d = \beta_{temp} \times \Delta_{temp} + \beta_{flush} \times \Delta_{temp} \times \text{shareflush} + \beta_{pit} \times \Delta_{temp} \times \text{sharepit} \\ + \beta_{piped} \times \Delta_{temp} \times \text{sharepiped} + \beta_{groundwater} \times \Delta_{temp} \times \text{sharegroundwater},$$

where the βs represent point estimates produced by regression diarrhoeal risk on temperature and its interaction with the four sub-groups of water and sanitation facilities. Δ_{temp} is the projected change in temperature for a given cell. 'Share flush', 'share pit', 'share piped', and 'share groundwater' is the proportion of the population in a given grid cell that has access to the respective water and sanitation facility.

(World Bank, 2017). The role of state and private actors as well as the effectiveness of different approaches depends on local technological, financial, institutional, social, and environmental factors [e.g.,] (Valcourt, Javernick-Will, Walters, & Linden, 2020). Our study suggests that among the environmental factors, temperature will become increasingly important. Furthermore, our estimates show that flush toilets are particularly effective in mitigating temperature-induced diarrhoea risks. On the other hand, pit latrines do not have any risk-reducing effects. This implies that in the context of rising temperatures building up and connecting people to sewerage systems would prove particularly valuable. Where this is not feasible (e.g., in many rural areas), improving existing and developing new non-networked technologies is central [e.g.] (Lourenço & Nunes, 2020).

We conclude by highlighting an important caveat of our research. Our study identifies short-run effects. The estimates therefore do not account for potential biological and behavioural adaptation processes that could help mitigate the negative effects of global warming (Kolstad & Moore, 2020; Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2016).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

We thank Michael Grimm and Matthias Schündeln as well as participants at the German Development Economics Conference 2021 for valuable feedback. We are grateful to Benn Sartorius for sharing the disaggregated data on access to drinking water and sanitation facilities.

Appendix A. Data sources

Tables A.1, A.2, A.3, A.4, Fig. A.1.

Appendix B. Robustness

Tables B.1, B.2, B.3, B.4.

Table A.1
DHS Waves included in sample.

Angola 2015	Ethiopia 2005	Malawi 2010	Senegal 2015
Benin 1996	Gabon 2012	Malawi 2016	Senegal 2016
Benin 2001	Ghana 1993	Mali 1995–6	Sierra Leone 2008
Benin 2011	Ghana 1998	Mali 2001	Sierra Leone 2013
Burkina Faso 1993	Ghana 2003	Mali 2006	South Africa 2016
Burkina Faso 1998	Ghana 2008	Mali 2012	Tanzania 1999
Burkina Faso 2003	Ghana 2014	Mozambique 2011	Tanzania 2010
Burkina Faso 2010	Guinea 1999	Namibia 2006	Tanzania 2015
Burundi 2010	Guinea 2005	Namibia 2013	Togo 1998
Burundi 2016	Guinea 2012	Niger 1998	Togo 2013–14
Cameroon 1991	Kenya 2003	Nigeria 2003	Uganda 2001
Cameroon 2004	Kenya 2008–9	Nigeria 2008	Uganda 2006
Cameroon 2011	Kenya 2014	Nigeria 2013	Uganda 2011
Chad 2014–15	Lesotho 2004	Rwanda 2005	Uganda 2016
Congo Democratic Republic 2007	Lesotho 2009	Rwanda 2010	Zambia 2007
Congo Democratic Republic 2013–14	Lesotho 2014	Rwanda 2014	Zambia 2013
Cote d'Ivoire 1994	Liberia 2005–06	Senegal 2005	Zimbabwe 1999
Cote d'Ivoire 1998	Liberia 2013	Senegal 2010–11	Zimbabwe 2005–6
Cote d'Ivoire 2011	Malawi 2000	Senegal 2012–13	Zimbabwe 2010–11
Ethiopia 2000	Malawi 2004	Senegal 2014	Zimbabwe 2015

Table A.2
Variables and sources

Variable	Source
Elevation	Amante and Christopher (2009)
Precipitation	CPC
Agricultural suitability	Galor et al. (2015, 2016)
Climate zones	Rubel et al. (2010)

Table A.3
Types of improved sanitation facilities and drinking water sources.

	Sanitation Facilities
Flush toilets	Flush toilet
	Connection to a piped sewer system
Improved pit latrine	Connection to a septic system
	Flush/ pour-flush to a pit latrine
	Pit latrine with slab
	Ventilated improved pit latrine
	Composting toilet
	Drinking Water Sources
Piped water	Piped water into dwelling
	Piped water into yard/plot
Groundwater	Public tap/standpipes
	Tubewell/boreholes
	Protected dug wells
	Protected springs (normally part of a spring supply)
	Rainwater collection
	Bottled water, if the secondary source used by the household for cooking and personal hygiene is improved

Classification is based on UNICEF (2017).

Table A.4
Climate Models.

Climate Model	Link to Description
ACCESS-ESM1-5	https://research.csiro.au/access/about/esm1-5/
BCC–CSM2-MR	https://gmd.copernicus.org/articles/14/2977/2021/
CanESM5	https://gmd.copernicus.org/articles/12/4823/2019/gmd-12-4823-2019.html
CanESM5-CanOE	https://gmd.copernicus.org/preprints/gmd-2019-177/
CMCC-ESM2	https://www.cmcc.it/models/cmcc-esm-earth-system-model
CNRM-CM6-1	http://www.umr-cnrm.fr/cmip6/spip.php?article11
CNRM-CM6-1-HR	http://www.umr-cnrm.fr/cmip6/spip.php?article11
CNRM-ESM2-1	http://www.umr-cnrm.fr/cmip6/spip.php?article10
EC-Earth3-Veg	https://gmd.copernicus.org/preprints/gmd-2020-446/
EC-Earth3-Veg-LR	https://cera-www.dkrz.de/WDCC/ui/cerasearch/cmip6?input=CMIP6.CMIP.EC-Earth-Consortium.EC-Earth3-Veg-LR.historical
FIO-ESM-2–0	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019JC016036
GISS-E2-1-G	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019MS002025
GISS-E2-1-H	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019MS002025
HadGEM3-GC31-LL	https://cera-www.dkrz.de/WDCC/ui/cerasearch/cmip6?input=CMIP6.HighResMIP.MOHC.HadGEM3-GC31-LL
INM-CM4-8	https://catalogue.ceda.ac.uk/uuid/17179dfb6bc24bbeaba902928c91e5c0
INM-CM5-0	https://cera-www.dkrz.de/WDCC/ui/cerasearch/cmip6?input=CMIP6.CMIP.INM.INM-CM5-0.piControl
IPSL-CM6A-LR	https://cmc.ipsl.fr/ipsl-climate-models/ipsl-cm6/
MIROC-ES2L	https://gmd.copernicus.org/articles/13/2197/2020/
MIROC6	https://gmd.copernicus.org/articles/12/2727/2019/gmd-12-2727-2019.html
MPI-ESM1-2-HR	https://gmd.copernicus.org/articles/12/3241/2019/
MPI-ESM1-2-LR	https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018MS001400
MRI-ESM2-0	https://www.jstage.jst.go.jp/article/jmsj/advpub/0/advpub_2019-051/_article/-char/en
UKESM1-0-LL	https://ukesm.ac.uk/cmip6/

Notes: All climate data accessed via the WorldClim database (https://www.worldclim.org/data/cmip6/cmip6climate.html). Links to descriptions of models accessed on 6 May 2022.

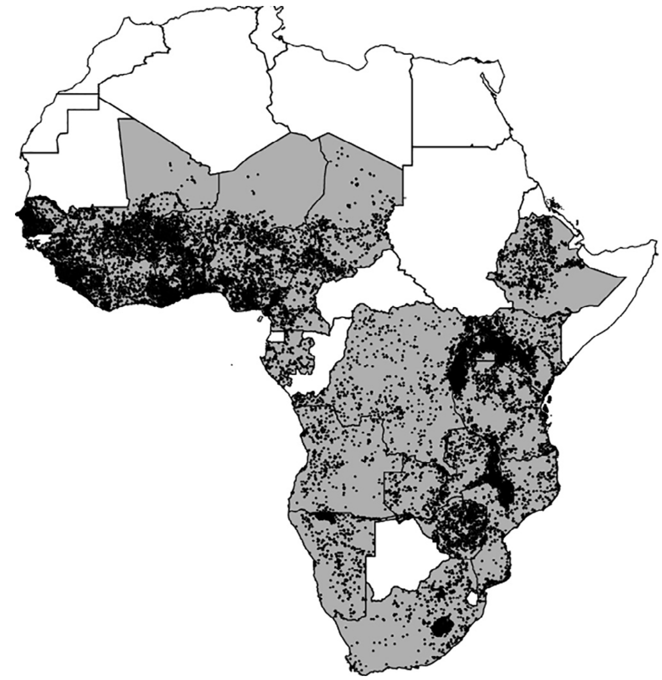

Fig. A.1. Figure depicts the countries covered in our sample (shaded grey) as well the locations of the individual DHS clusters (dots).

Table B.1
Female only: Temperature and Diarrhoea.

	Diarrhoea during last 15 days				
	(1)	(2)	(3)	(4)	(5)
Temperatures 15-day window current year (SD)	0.018***	0.017***	0.016***		
	(0.006)	(0.006)	(0.006)		
Temperatures 15-day window past year (SD)				0.002	
				(0.005)	
Temperatures 15-day window next year (SD)					0.006
					(0.006)
Controls child	Yes	Yes	Yes	Yes	Yes
Controls mother	No	Yes	Yes	Yes	Yes
Controls household	No	Yes	Yes	Yes	Yes
Controls location	No	No	Yes	Yes	Yes
Controls historical temperatures	Yes	Yes	Yes	Yes	Yes
Country×climate zone×year×month FE	Yes	Yes	Yes	Yes	Yes
Observations	300,014	300,014	300,014	300,014	300,014
R-squared	0.084	0.086	0.087	0.087	0.087

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

Table B.2
Males only: Temperature and Diarrhoea.

	Diarrhoea during last 15 days				
	(1)	(2)	(3)	(4)	(5)
Temperatures 15-day window current year (SD)	0.015***	0.015***	0.012**		
	(0.006)	(0.006)	(0.006)		
Temperatures 15-day window past year (SD)				0.007	
				(0.005)	
Temperatures 15-day window next year (SD)					0.001
					(0.005)
Controls child	Yes	Yes	Yes	Yes	Yes
Controls mother	No	Yes	Yes	Yes	Yes
Controls household	No	Yes	Yes	Yes	Yes
Controls location	No	No	Yes	Yes	Yes
Controls historical temperatures	Yes	Yes	Yes	Yes	Yes
Country×climate zone×year×month FE	Yes	Yes	Yes	Yes	Yes
Observations	296,508	296,508	296,508	296,508	296,508
R-squared	0.077	0.079	0.080	0.080	0.080

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

Table B.3
Robustness: Temperature and Diarrhoea All regressions run with full set of controls (i.e., setup presented in Table 3, column (3)).

	Diarrhoea during last 15 days					Wasting	Height
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperatures 15-day window current year (SD)	0.013***	0.014***	0.013***	0.014***	0.012***	0.019***	−0.011
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.015)
Robustness	Additional controls	Malaria index	Long-run temperature	Clustering	Weighting	Wasting	Height
Controls child	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls mother	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls household	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls location	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls historical temperatures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×climate zone×year×month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	596,522	596,522	596,522	596,522	596,522	393,612	334,393
R-squared	0.082	0.081	0.081	0.079	0.079	0.052	0.159

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.
In column (1), we add the following controls: distance to coastline, capital, nearest rivers and land border, respectively.
Column (2) accounts for the local climatic malaria suitability index developed in and.
In column (3) we control for the 5-year average temperature conditions that prevail in the two-week pre-interview window.
Standard errors in column (4) are clustered by administrative regions.
Observations in column (5) are not weighted.

Table B.4
Robustness: Less restrictive fixed effects All regressions run with full set of controls (i.e., setup presented in Table 3, column (3)).

	Diarrhoea during last 15 days						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperatures 15-day window current year (SD)	0.021*** (0.003)	0.017*** (0.003)	0.017*** (0.003)	0.018*** (0.004)	0.016*** (0.004)	0.013*** (0.004)	0.013*** (0.004)
Controls child	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls mother	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls household	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls location	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls historical temperatures	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Fixed effect variations						
Country FE	Yes	Yes	Yes	No	No	No	No
Month FE	Yes	Yes	Yes	No	No	No	No
Year FE	No	Yes	Yes	No	No	No	No
Climate zone FE	No	No	Yes	No	Yes	No	Yes
Country×month FE	No	No	No	Yes	Yes	No	No
Country×year×month FE	No	No	No	No	No	Yes	Yes
Observations	596,522	596,522	596,522	596,522	596,522	596,522	596,522
R-squared	0.065	0.067	0.068	0.057	0.059	0.075	0.075

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

Appendix C. Supportive Evidence

Table C.1.

Table C.1
Heterogeneities across age groups.

	Diarrhoea during last 15 days
Aged [0,1] × Temperatures 15-day window current year (SD)	0.003 (0.005)
Aged (1,2]] × Temperatures 15-day window current year (SD)	−0.000 (0.005)
Aged (2,3]] × Temperatures 15-day window current year (SD)	0.022*** (0.005)
Aged (3,4]] × Temperatures 15-day window current year (SD)	0.025*** (0.005)
Aged (4,5]] × Temperatures 15-day window current year (SD)	0.024*** (0.005)
Historical temperatures	Yes
Controls child	Yes
Controls mother	Yes
Controls household	Yes
Controls location	Yes
Country×climate zone×year×month FE	Yes
Observations	596,522
R-squared	0.082

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at DHS cluster level and reported in parentheses. Child controls include gender, age and birth order fixed effects. Mother controls encompass dummies for age, marital status, and educational. Household controls are fixed effects for urban residence, wealth index, access to flush toilet, and safe drinking water. Location controls include climate zones, historical and recent precipitation, agricultural suitability, (absolute) latitude, longitude, and elevation. 'Historical temperatures' capture the temperature average over the 15-day window in the 10 years preceding the year of the interview.

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