The impact of in-utero exposure to ambient temperature on maternal health, infant health, and population composition

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Preface

This thesis entails one methodological chapter (Chapter II) and three empirical studies (Chapters III, IV, V). These chapters are accompanied by an introduction and discussion to present the motivation for this work, contextualize it within a broader body of literature, and synthesize findings across different settings. Acknowledgments, references, and appendices are presented after each chapter.

Chapter I introduces the background of this research and its relevance, presents the objectives and contributions of this thesis, and provides an overview of the following chapters.

Chapter II presents a methodological framework to guide the data extraction and statistical analysis of micro-level temperature-birth linkages. The framework is applied in the following empirical chapters.

Chapter III is an empirical study that investigates the impact of temperature exposure during gestation on antenatal care visits in 52 LMICs.

Chapter IV is an empirical study that investigates the impact of in-utero temperature exposure on the sex ratio at birth in Sub-Saharan Africa and India.

Chapter V is an empirical study that investigates the impact of prenatal heat exposure on infant mortality in Mali, after presenting a conceptual framework on mechanisms.

Chapter VI reflects on the implications of the Demographic and Health Survey (DHS) Program's termination for climate-population research, synthesizes emerging findings across the empirical chapters, discusses limitations, and presents emerging questions for future research.

Co-authorship statement

The following statement outlines the contributions made by myself and the co-authors in each chapter. The relevant information for each chapter is also found on the title page of each chapter.

Chapter I: Introduction: Solo-authored, no co-authorship contributions to declare.

Chapter II: Data, measurement, and modelling issues for temperature-birth linkages: Solo-authored, no co-authorship contributions to declare.

Chapter III: Extreme heat reduces antenatal care visits in vulnerable low- and middle-income countries: Solo-authored, no co-authorship contributions to declare.

Chapter IV: Temperature and sex ratios at birth: This chapter is based on first-authored work with co-authors Joshua Wilde[1, 2, 3, 4, 5], Anna Dimitrova[6], Ridhi Kashyap[1, 2, 7], Raya Muttarak[8]. I designed and conceptualized the research, cleaned the data, conducted all statistical analyses, made all figures and tables, and wrote the paper. Joshua Wilde and Raya Muttarak contributed to conceptualization. Anna Dimitrova downloaded the data and merged environmental and survey data. Raya Muttarak assisted during the journal review process.

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Chapter V: Survival of the fittest: How prenatal heat exposure reduces infant mortality in Mali: This chapter is based on co-authored work with Liliana Andriano[1] as second author. I conceptualized the research, developed the framing, downloaded the environmental data, merged it with the survey data, cleaned the data, conducted all statistical analyses, made all figures and tables, and wrote the paper. Liliana Andriano contributed to the conceptualization of the research and provided writing edits.

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Chapter VI: Discussion: This chapter is based on solo-authored work and co-authored work.

All sections are solo-authored work, except Section 1, which is based on co-authored work, which I have altered for the purpose of this thesis.

Section 1 draws on first-authored work with co-authors Aasli A. Nur[1,2,3], Kerry L.D. MacQuarrie[4], Joshua K. Wilde[1,2,5,6,7], Elizabeth A. Sully[8], Mahesh Karra[9], Ursula Gazeley[1,2], Ben M. John[5,10], Livia Montana[11,12].

I conceptualized the article and wrote it. Joshua Wilde and Livia Montana contributed to the conceptualization. Aasli Nur conducted a bibliometric analysis. All co-authors provided comments and writing edits.

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Our opinion article with the title “Moving towards equitable data infrastructure and research integrity after the termination of the DHS Program” is available publicly as a preprint (https://doi.org/10.31235/osf.io/ka3r5_v1). The preprint discusses the implications of the DHS Program’s termination for research in demography, public health, and other disciplines more generally. The work is based on collaboration between demographers, economists, epidemiologists, and the former Deputy Director of the DHS Program (Livia Montana) and Director of Research (Kerry MacQuarrie).

However, for this chapter, I have changed the scope of the article and adapted it to specific issues in climate-population research. Based on the preprint to which co-authors contributed as described, Section 1 in this chapter was entirely written by myself without contributions from co-authors. The preprint’s bibliometric analysis that was conducted by Aasli Nur is not included in this thesis, except for a result that I cite from this analysis with clear reference to the preprint.

Contents

Abstract

Climate change is leading extreme heat episodes to increase in frequency, intensity, and duration, posing a threat to population health especially in low- and middle-income countries (LMICs). In this context, extreme heat has been linked to a range of adverse birth outcomes, pointing to the sensitivity of exposure during the prenatal period. With growing populations vulnerable to extreme heat, advancing our understanding of how extreme heat impacts maternal and infant health is urgent. However, several knowledge gaps persist. Little is known about the underlying mechanisms and critical temperature thresholds that link extreme heat and maternal and infant health outcomes, the implications that these relationships have for population composition, and the extent to which heat impacts lead to socially stratified responses. In addition, various methodological approaches have led to inconsistency in findings. In this thesis, I investigate the impact of in-utero exposure to ambient temperature on maternal health, infant health, and population composition. First, I present a comprehensive methodological framework that guides the statistical analysis of temperature impacts on births with a plausible causal identification strategy. I employ this framework rigorously in three applications, the first of which investigates the impact of temperature on antenatal care visits across 52 LMICs. Results show that extreme heat impacts health-related behaviour, by reducing antenatal care visits particularly for mothers in Sub-Saharan Africa who already face significant barriers in accessing healthcare. The second application studies how in-utero temperature exposure affects the sex ratio at birth, as an indicator of population composition. Exploiting socio-cultural differences in son preference norms, I show that extreme heat reduces male birth probability in Sub-Saharan Africa and India through male-biased pregnancy loss and reductions in induced sex-selective abortions of female offspring. The third application investigates a postnatal outcome, using a case study in Mali. Here, I develop a conceptual framework on biological and behavioural pathways and show that prenatal heat exposure reduces infant mortality, most likely through intensified prenatal selection of weaker offspring. Overall, this work underlines the multiple pathways through which human reproduction and health are sensitive to the environment. The findings from this thesis serve to inform policy and intervention in vulnerable populations to safeguard the health and wellbeing of mothers and infants and prevent widening health inequities in a warming climate.

Chapter I: Introduction

Co-authorship note: This chapter is based on solo-authored work. No co-authorship contributions to declare.

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Chapter I: Introduction

1 Background

Rising temperatures pose a threat to the health and wellbeing of populations globally, but especially in low- and middle-income countries (LMICs). Estimations show that even under a 1.5°C pathway of future warming, globally 52% of people born in 2020 will experience unprecedented exposure to heatwaves over their lifetime by 2100 (Grant *et al.*, 2025). Climate change had already increased the number of global temperature records expected in 2000 to 2010 from 0.1 to 2.8 (Rahmstorf and Coumou, 2011). Given this rapid environmental change for populations around the globe, scholarship in the fields of demography, population health, epidemiology, and economics has embarked on the quest to understand how temperature impacts health in different contexts for different subgroups of the population (Gasparrini and Armstrong, 2011; Grace, 2017; Burke *et al.*, 2018; Green *et al.*, 2019).

The study of climate impacts on population health and wellbeing was enabled by the advent of remote sensing and research developed rapidly in the last decade. In the 1960s and 1970s, earth observation satellites began orbiting the planet to collect vast amounts of information on environmental conditions around the globe (National Research Council, 1998; Kugler *et al.*, 2019). These data collections revolutionized the study of climate-population interactions. Publicly available environmental data products from remote sensing technology can now be linked with georeferenced population records, processed with powerful computational tools (Kugler *et al.*, 2019). More recently, advanced statistical models (Dell, Jones and Olken, 2014) and existing theoretical concepts such as the life-course approach have been applied to the study of climate impacts on populations (Grace, Billingsley and Van Riper, 2020). Together, these developments have made it possible to link individuals' health outcomes with fine-resolution data on environmental conditions across their life-course in ways that can be interpreted as causal.

Pregnant mothers and infants are particularly vulnerable to the adverse effects of extreme heat (Segal and Giudice, 2022; Faurie, 2023; Arunda *et al.*, 2024; Schapiro *et al.*, 2024) and have been included as a particularly vulnerable population in the Intergovernmental Panel on Climate Change's Sixth Assessment Report (Pörtner et al., 2022). Exposure to extreme heat during pregnancy has been associated with an increased risk of a range of adverse birth outcomes, including stillbirth, preterm birth, and low birthweight (Strand, Barnett and Tong, 2012; Chersich *et al.*, 2020; McElroy *et al.*, 2022). The in-utero period links both maternal and infant health in the context of extreme heat, with potential consequences for maternal morbidity (Jiao *et al.*, 2023) and the infant's health and development through the life-course (Isen, Rossin-Slater and Walker, 2017; Bratti, Frimpong and Russo, 2021; Brink *et al.*, 2024). Evidence on the concrete physiological mechanisms that explain how extreme heat increases the risk of adverse birth outcomes is urgently required and still emerging. Existing studies point to the difficulty of thermoregulation during pregnancy, where the fetus is entirely dependent on maternal regulation, as well as blood and oxygen flow being diverted away from the placenta, which can induce fetal heart strain (Bonell *et al.*, 2022; Samuels *et al.*, 2022).

As extreme heat poses significant risks for a healthy pregnancy as well as infant health and survival, this prompts concerns about climate risks stalling urgent global progress to improve maternal and infant health in LMICs. Monitoring of progress on population health indicators under the Sustainable Development Goals (SDGs) suggests that improvement rates on maternal and neonatal mortality indicators are stalling (WHO, 2025). Between 2015 and 2023, the maternal mortality (SDG 3, Target 1) ratio dropped from 228 deaths per 100,000 live births to only 197 – a figure yet nearly triple the SDG target of 70 that should be achieved by 2030. Limited progress was especially evident in Sub-Saharan Africa and Southern Asia, which carry the largest burden of maternal deaths globally with almost 90 % of deaths. In 2023, 50 % of pregnant reproductive-age women in low-income countries, and 34.8 % in lower middle-income countries still attended less than four ANC visits during pregnancy by any provider[1] (UNICEF, 2025), despite the updated global WHO recommendation of at least eight visits since 2016 (WHO, 2016). Global neonatal mortality (SDG 3, Target 2) decreased by 12 % but progress has slowed, too. The annual rate of neonatal mortality reduction was 3 % between 2000 and 2015, but only 1.6 % thereafter (United Nations Department of Economic and Social Affairs, 2025). Mitigating and addressing the adverse consequences of extreme heat remains a priority to prevent a widening of global health inequities and ensure that further necessary progress is made on maternal and infant health targets and health dimensions not captured by the SDGs.

Understanding how extreme heat impacts maternal and infant health is crucial to motivate climate mitigation and enable adaptation in LMICs, but several knowledge gaps persist. First, the climate-health literature has advanced insight on temperature effects on adult mortality (Ballester *et al.*, 2023; Matthews *et al.*, 2025). But mortality in-utero and in the first year of life has only received limited attention (Kudamatsu, Persson and Strömberg, 2012; Auger *et al.*, 2017; Chersich *et al.*, 2020), even though it is closely linked with maternal health and infant wellbeing across the life-course. Second, changes in *population composition* have mostly been studied in the context of climate-induced migration (Cattaneo and Peri, 2016; Abel *et al.*, 2019; Hoffmann *et al.*, 2020), and heat-related adult mortality, but less so in the context of prenatal mortality and fertility (Barreca, Deschenes and Guldi, 2018; Hajdu and Hajdu, 2020; Conte Keivabu, Cozzani and Wilde, 2024). Here, most studies have focused on high-income populations, with a few exceptions (Thiede *et al.*, 2022; Gray and Thiede, 2024). High-income populations face a lower burden of both maternal and infant morbidity but also on average lower heat risks, so evidence on LMICs is urgently needed. Third, evidence on how heat impacts on maternal and infant health are *socially stratified* is still limited. While studies point to the important role of socioeconomic status (SES) (Conte Keivabu and Cozzani, 2022; Andriano, 2023), many other factors could increase vulnerability or resilience to extreme heat. Ultimately, these differences can lead to inequality in the extent to which extreme

[1] Country classification is based on the World Bank's classification, see UNICEF Data Warehouse.

heat affects health outcomes between different social groups. Fourth, the *mechanisms* that link extreme heat and maternal and infant health are poorly understood. Most studies establish a relationship but fail to investigate relevant pathways, with some exceptions (Barreca, Deschenes and Guldi, 2018; Andriano, 2023; Hajdu and Hajdu, 2023). In addition, existing studies that do consider pathways largely ignore that not only biological health responses could matter, but also maternal behaviour. Fifth, even though statistical methods for causal identification (Dell, Jones and Olken, 2014) and conceptual frameworks for climate-reproductive health studies (Grace, Billingsley and Van Riper, 2020) exist, their application has been *inconsistent*. For example, even in the same areas under study, inconsistent findings have emerged, and extreme heat has been linked with both fertility increases (Gray and Thiede, 2024) and decreases (Barreca, Deschenes and Guldi, 2018; Thiede *et al.*, 2022). It is possible that discrepancies in methodological approaches explain these results. Overall, though rapid progress has been made in the study of temperature impacts on maternal and infant health and population composition, important theoretical questions remain, and methodological best-practice remains unclear.

This thesis investigates the impact of in-utero temperature exposure on maternal health, infant health, and population composition. To guide the study of prenatal temperature impacts on maternal and infant health, I present a methodological framework that responds to inconsistent measurement and modelling approaches in this literature. The framework provides a practical guide for the linkage of gridded environmental data with micro-level birth records and the unique statistical analysis issues that arise in the identification of temperature impacts on births. In my empirical chapters, I apply this framework rigorously to study outcomes during pregnancy, at birth, and postnatally. The empirical chapters investigate the impact of in-utero temperature exposure on 1) antenatal care (ANC) visits, 2) sex ratios at birth (SRBs), and 3) infant mortality. For these studies, I merge birth histories from the georeferenced Demographic and Health Surveys (DHS) in LMICs with daily, high-resolution temperature data for each pregnancy at the mother’s location. The findings show that extreme heat may function through three distinct mechanisms that are context-specific and health-relevant: Extreme heat may reduce healthcare visits of pregnant mothers, intensify male-biased prenatal selection, and decrease induced sex-selective abortions of females in son preference contexts. Overall, the thesis makes novel theoretical, conceptual, and methodological contributions to the climate-population literature, by focusing on important barely investigated outcomes, identifying underlying health and behavioural mechanisms, and highlighting how impacts are socially stratified. The findings have important implications for population composition, maternal and infant health, global and within-population health inequity, and gender equality in the context of climate change.

The thesis should be viewed as theoretically embedded into the concepts of reproductive justice and climate justice. I argue that the exposures and impacts associated with extreme heat – as a climate change related stressor – are socially stratified. Therefore, extreme heat (re)produces reproductive (health) inequality between populations, and social and sociodemographic groups. Reproductive justice entails three main principles: The right not to have a child, the right to have a child, and the right to parent children in safe and healthy environments (Ross and Solinger, 2017). Climate justice, in the context of health, is centered on the relationship between climate change impacts, social dimensions, adaptive capacities, and biological sensitivities (Bolte *et al.*, 2023). In this sense, climate justice is deeply connected to health equity and social determinants of health. This thesis is concerned with how extreme heat stratifies maternal and infant health because of inequalities in exposure, adaptive capacity, and the ability to recover. These inequalities constitute differences in both the allocation of environmental exposure and the impact that exposure has (Squires and Hartman, 2013; Torche and Nobles, 2024) on the maternal and infant health outcomes of individuals and population groups. Even for climate-health relationships that are driven by biological health mechanisms, underlying the relationship are often social injustices (Grzywacz and Fuqua, 2000; Muller, Sampson and Winter, 2018). Extreme heat exposure and impacts have been shown to differ by age, education, income, race/ethnicity, housing conditions, and other social and biological determinants (Ellena *et al.*, 2020; Conte Keivabu and Cozzani, 2022; Rastogi *et al.*, 2023; Conte Keivabu, Basellini and Zagheni, 2024; Li *et al.*, 2025). My work considers that extreme heat as an environmental exposure could impact the reproduction and reproductive health of some social groups disproportionately – and particularly of social groups that are already disproportionately affected by both reproductive (health) inequalities and climate risks.

Advancing our understanding of how extreme heat impacts maternal health, infant health, and population composition is of interest to both science and policy across different disciplines. First, this thesis helps uncover how population composition, dynamics, and health are embedded in and shaped by the natural environment. Hence, the findings also contribute to our understanding of how populations and their health will evolve under climate change in the future. Second, the thesis underlines how extreme heat as an environmental exposure reproduces important reproductive health inequities globally and within populations. Therefore, the insights from this work can serve to not only inform targeted interventions that protect pregnant mothers and their offspring from extreme heat, but also address reproductive and climate health inequalities, and help adapt societies to climate-driven changes in population composition. In addition, because the in-utero period can shape later life health and development (Barker, 1990; Almond and Currie, 2011), the findings and methodology developed in this thesis lay a foundation for future work on the role of prenatal temperature exposure for outcomes in childhood and adulthood, including morbidity and mortality, labor, and socioeconomic attainment. Overall, this thesis aims to address both scholars and policymakers in demography, population health and epidemiology, sociology, and climate and environmental studies.

The thesis is structured as follows. Chapter I outlines the thesis's rationale by presenting six main objectives and the theoretical and methodological contributions this thesis makes to the study of extreme heat impacts on maternal health, infant health, and population composition, in line with the gaps in the current literature identified above. At the end of the chapter, I present an overview of the thesis chapters. Then, Chapter II proposes a methodological framework for environment-birth data linkage, Chapter III to V are empirical applications of this framework for the study of in-utero temperature impacts on ANC, SRBs, and infant mortality. Chapter VI concludes the thesis with a synthesis of findings, a reflection on climate-population research in the context of the DHS Program's termination in 2025, and a discussion of emerging questions for future research.

2 Objectives and contributions

I aim to contribute to the literature on environmental impacts on health and demographic outcomes by achieving six main objectives, as presented in this section. The objectives summarize goals across the empirical chapters. Addressing these objectives advances our understanding in this field of study through theoretical, conceptual, and methodological contributions. Overall, this thesis makes novel contributions to the environmental demographic and sociological literature, demonstrating, through a rigorous methodological framework, that heat exposure can lead to socio-behavioural and physiological health responses that affect maternal health, infant health, and population composition. Across LMICs, these responses can be biological and behavioural, context-specific, and socially stratified.

2.1 Objective 1: To investigate in-utero temperature impacts on early life mortality

While evidence on the impact of extreme heat on population health has grown rapidly, the consequences of extreme heat for early life[2] mortality are still poorly understood. Most studies on the impact of extreme heat on mortality have focused on adult and old-age

[2] In line with existing literature, I refer to the "early life" period as encompassing the in-utero period and the first few years of childhood.

mortality (Matthews *et al.*, 2025) – an important focus as findings show larger excess mortality for higher age groups (Ballester *et al.*, 2023; Scovronick *et al.*, 2024). Regarding prenatal and early life mortality, some evidence suggests that extreme heat increases neonatal mortality in LMICs (Dimitrova *et al.*, 2024), and stillbirths (Auger *et al.*, 2017; Chersich *et al.*, 2020; McElroy *et al.*, 2022), but for miscarriages high-quality evidence is limited. Overall, further studies are needed to comprehensively understand where and how extreme heat impacts early life mortality.

Understanding how heat exposure changes prenatal mortality and mortality in the first years of life is important for demographic and population health inquiry for four main reasons. First, insults early in life can have significant consequences for health and development across the life-course. Second, prenatal and early life insults can induce selection through mortality or scarring, shaping the composition and outcomes of cohorts years later. Third, prenatal and early life mortality are closely linked to maternal health through pregnancy loss and bereavement. Fourth, they also matter for reproductive inequality if there are differences in abortion and bereavement experiences between social groups.

This thesis moves beyond the literature's current focus on adult mortality, centering the investigation of temperature impacts on prenatal and infant mortality in the first year of life. Linking changes in prenatal and infant mortality with temperature advances our understanding of how population composition and the health of cohorts may develop in a rapidly changing climate.

2.2 Objective 2: To identify in-utero temperature impacts on population composition

While the reproductive health literature documents the link between prenatal heat exposure and a range of adverse birth outcomes, few studies explain how extreme heat is directly linked to population composition. For example, in-utero heat exposure has been linked with an increased risk of spontaneous abortion and stillbirth, low birthweight, and preterm birth (Andalón *et al.*, 2016; Chersich *et al.*, 2020; McElroy *et al.*, 2022; Andriano, 2023; Hajdu and Hajdu, 2023). Due to this focus on adverse birth outcomes, and especially live birth outcomes, the population composition effects of extreme heat in terms of early life mortality are poorly understood. While some studies undertake direct estimations of the effect of extreme heat on early life mortality (Lakhoo *et al.*, 2022; Dimitrova *et al.*, 2024), these studies do not illuminate in-utero exposure effects because they focus on postnatal heat exposure.

This thesis makes several theoretical contributions to the literature by identifying temperature impacts on outcomes that directly influence population composition. First, Chapter IV analyzes how temperature affects the *SRB*. This is the first large-scale analysis of temperature impacts on the SRB, to the best of my knowledge. The SRB indicates the sex balance at birth and is closely linked to prenatal mortality. The sex balance at birth matters for sex balances at later ages, marriage dynamics, and population growth. Chapter V analyzes the impact of prenatal heat exposure on *infant mortality*. The chapter provides the first single-country study investigating this relationship, besides a working paper that mainly focuses on postnatal heat impacts in a large set of LMICs (Geruso and Spears, 2018). Hence, my analysis helps us understand how population composition in the first year of life may be changed by prenatal heat exposure. If changes in infant mortality are driven by changes in prenatal selection, this could point to compositional changes in the cohort that survives to birth, in the first year of life, and potentially thereafter. Furthermore, heat-induced changes in infant mortality may also imply changes in the population's age structure and growth. To summarize, the thesis investigates how prenatal heat exposure impacts the SRB and infant mortality as indicators of population composition that have barely been investigated in the context of temperature.

2.3 Objective 3: To identify how in-utero heat impacts are socially stratified in LMICs

Identifying how the effect of temperature on population health is socially stratified is a major contribution of this thesis. From a sociological perspective, this stratification informs understandings of climate and reproductive justice, and potentially has implications for outcomes across the life-course. The thesis identifies vulnerable population groups that are disproportionately affected by the negative impacts of extreme heat on health. This knowledge can also inform targeted policy and intervention for climate adaptation. Sources of unequal impacts of extreme heat can be economic, social, political, and geographic (Ellena *et al.*, 2020; Rastogi *et al.*, 2023; Badakhshan *et al.*, 2025; Li *et al.*, 2025).

I identify vulnerable population groups from two different perspectives. First, my empirical work highlights inequities between global regions and countries to identify populations where adverse heat impacts are intensified, suggesting that extreme heat may deepen global health inequalities. Second, the thesis also highlights inequities between sociodemographic subgroups within a population. The thesis also makes group differences comparable. I interpret temperature effect in absolute terms (the effect of one additional heat day in the pregnancy) and in relative terms, taking the local temperature distribution into account (the effect adjusted by the standard deviation of temperature in each subsample).

In these heterogeneity analyses, I use a broad range of underutilized information on maternal and infant characteristics to analyze group differences. The literature concerned with temperature impacts on health often considers differences by socioeconomic status (SES) and urban-rural residence as factors that can shape vulnerability to heat impacts (Conte Keivabu, 2022; Conte Keivabu and Cozzani, 2022; Andriano, 2023). I move beyond this narrow focus and consider a range of individual-level factors that have not been explored extensively in the context of the outcomes I study. They include social-biological factors, healthcare infrastructure, and social norms.

2.4 Objective 4: To identify mechanisms that explain temperature impacts on the outcomes under study

Further, the thesis makes important methodological and theoretical contributions by showing how mechanisms can be identified. The approach of many studies on the relationship between extreme heat and adverse birth outcomes is to a) establish a relationship between exposure and outcome and b) examine heterogeneity in this relationship by SES and other factors (Conte Keivabu and Cozzani, 2022; Andriano, 2023). By contrast, my approach advances our understanding not only of the causal linkages between heat exposure and population health outcomes. It also provides insight into *how* these linkages shape the relationship between heat exposure and maternal and infant health outcomes and population composition – beyond simply describing heterogeneous responses.

The challenge here is that the DHS – and other large, publicly available social and demographic surveys in LMICs – do not collect direct information on mechanisms that could be tested. The limitation of the biomarker module is that it collects information only at the time of interview. But many of the relevant factors that could explain mechanisms are time-variant across the mother’s reproductive life-course. For example, valuable data could include longitudinal information on factors such as hydration and nutrition of the mother, heart rate, gestational length, body composition, lifestyle patterns, hours and times of outdoor exposure, physical activity, distance to the health facility, availability of antenatal care, self-reported mental and physical wellbeing, social networks, access to cooling technologies at the home and workplace, social support during pregnancy and in the postpartum period, and more. Such information would allow me to adjust exposure measurements meaningfully, and investigate the role of a range of health, social, and behavioural determinants. However, these factors are either not reported or only once at the time of interview (e.g., anemia, occupation).

Noteworthy are three other data sources that have made important advancements for the study of mechanisms, but each has their own limitations, too. First, the Health and Demographic Surveillance Systems (HDSS) are intensive, longitudinal data collections across 29 African and Asian sites (Herbst *et al.*, 2021). However, the limitation of the HDSS is that temperature variation is limited to the 29 sites, which can challenge the causal identification of climate impacts on demographic and health outcomes with fixed effects[3]. Second, observational cohort studies that collect information on maternal and infant health under heat exposure can provide direct insight into physiological pathways. Bonell *et al.* (2022) provide one such study at a field location in The Gambia where heart rate, skin temperature, and fetal heart rate of pregnant subsistence workers were measured. Such research though resource-intensive, is immensely valuable for advancing our understanding of physiological mechanisms. Third, more qualitative research is needed to illuminate perceptions and behavioural responses to extreme heat by pregnant and postpartum mothers, with embedding in their social networks and institutional settings. Qualitative research methodology has been focused on symptoms and perceptions of heat stress by pregnant individuals (Spencer *et al.*, 2022; Kadio *et al.*, 2024). More work is needed to understand (lack of) adaptive behaviour (Scorgie *et al.*, 2023), and also specifically health-related behaviour. In summary, while notable advancements in data collection have been made, further innovation in data and methodology is necessary to understand mechanisms across diverse populations.

Given the limited availability of direct information on time-varying social and health factors, the study of mechanisms is a major contribution of this thesis. This contribution is both a methodological and theoretical one. Methodologically, the thesis provides examples of how mechanisms can be identified. Theoretically, it also contributes to the

[3] I explain in Chapter II that the place-time fixed effects that isolate the plausibly random component of temperature require sufficient temperature and outcome variation within the same location over time and across locations, as they absorb a substantial amount of variation to control for seasonality, and annual trends and shocks.

literature by advancing our understanding of several biological and behavioural mechanisms in the context of maternal and infant health in LMICs.

My theoretical contributions on mechanisms are unique for each chapter. In Chapter III, I investigate whether ANC visits are linked with extreme heat. This moves the focus of the climate-maternal health literature beyond *physiological* responses to a maternal *behavioural* response. Reductions in ANC visits could in turn have relevant consequences for other maternal and newborn health outcomes. In Chapter IV on SRBs, I test both a biological response (male-biased pregnancy loss) and a behavioural response (induced abortion of females) to heat exposure. In Chapter V, I investigate the effect of prenatal heat exposure on infant mortality. This study moves beyond heterogeneity analyses and instead develops a theoretical framework on mechanisms. The framework sets out different pathways that could explain the relationship between prenatal heat exposure and infant mortality. It may be applied to other climate exposures and infant health outcomes, too. Together, these studies inform how both biological health and behavioural responses to extreme heat can impact maternal health, infant health, and population composition. The studied pathways focus on a) changes in ANC, b) spontaneous pregnancy loss, c) sex-selective induced abortions.

My methodological contribution here is showing that four types of information can aid the urgent identification of mechanisms in the absence of direct information on them: heterogeneous responses across sociodemographic groups, heterogeneous responses across geographic and socio-cultural contexts, identification of sensitive exposure windows, and assessment of the magnitude of estimated effects. While such tests with DHS data cannot directly confirm mechanisms, they can help point to plausible pathways and rule out implausible ones – particularly in their combination.

2.5 Objective 5: To develop a methodological framework for temperature-birth linkage

As a methodological and conceptual contribution, I develop a framework for the linkage of high-resolution, gridded environmental data with micro-level birth records from georeferenced surveys (Chapter II). I build on three noteworthy existing frameworks for micro-level linkage of birth records with gridded environmental data but extend them in several directions. First, Grace (2017) argued that fertility and reproductive health in poor countries cannot be understood without considering climate. Grace gave an overview of labor, nutrition, and income mechanisms, relevant data sources, and modelling suggestions. Second, Grace, Billingsley and Van Riper (2020) introduced a life-course perspective and epidemiological terminology on sensitive exposure periods into the study of climate impacts on maternal and child health. Third, Dell, Jones and Olken (2014) laid out a fixed effects modelling strategy for the causal identification of temperature impacts on a range of economic outcomes, which was later applied to the study of temperature and fertility (Barreca, Deschenes and Guldi, 2018).

The methodological framework presented in this thesis focuses on the distinct data, measurement, and modelling issues that arise when modelling temperature impacts on maternal and infant outcomes. Temperature variation is cyclical in nature, which needs to be reflected accordingly in both measurement construction and the modelling approach. Chapter II critically evaluates the different measurement and modelling approaches used in the literature that have produced inconsistent results. I argue for the use of a method that exploits the quasi-random variation in temperature over time and space and reveals non-linear temperature impacts across different heat intensity levels. The framework is grounded in theory about the nature of temperature variation and its health impacts, empirical evidence, and triangulation based on findings from my own empirical work.

I consistently apply the developed methodological framework in the empirical chapters to demonstrate how it facilitates consistent causal identification of temperature impacts on both behavioural and biological mechanisms – across diverse study contexts. The framework aims to be specific to the study of extreme heat. But the underlying methodological issues discussed in this chapter are relevant to a range of environmental exposures and outcomes.

2.6 Objective 6: To exploit different study settings to identify temperature impacts and mechanisms

This thesis makes conceptual contributions by demonstrating how study settings can be chosen strategically to advance our understanding of how temperature affects maternal health, infant health, and population composition. My thesis showcases how three different approaches to choosing the study context can enrich our understanding of *where* temperature impacts health outcomes and population composition, but also of *how* the underlying mechanisms are at play.

The first approach, applied in Chapter III, conducts a global analysis. This chapter highlights inequities between countries and larger world regions by estimating temperature impacts on ANC across 52 LMICs. This approach is useful to describe how significantly the impact of temperature can vary across different contexts and motivate the focus of future research.

The second approach, applied in Chapter IV, leverages a comparative analysis. To identify relevant mechanisms, I compare the effect of temperature on the SRB in Sub-Saharan Africa and India. This chapter demonstrates how a comparative analysis can leverage differences in social norms to distinguish biological and behavioural mechanisms or responses to heat. This approach can also highlight how the geographic and social context shape the relationship of interest.

The third approach, applied in Chapter V, demonstrates the usefulness of single-country studies. This approach centers on a theoretical question and then leverages a context where the hypothesized mechanism can be feasibly identified. I conceptualize Mali as a setting where the hypothesized mechanism is relatively likely to be at play, given its lower baseline health and higher heat exposure compared to other settings. In addition, detailed birth information from the Mali 2018 DHS makes this study feasible.

On the one hand, this objective constitutes a conceptual contribution – by illustrating three different approaches to contextual analysis – and an empirical one, by enhancing our understanding of social stratification in the relationships under study (objective 3) and the underlying mechanisms at play (objective 4).

3 Overview of thesis chapters

The thesis is structured as follows. First, Chapter I has provided an introduction to the study of climate impacts on maternal health, infant health, and population composition. It situated this thesis into a body of research that responds to the need to understand climate change impacts on populations across the globe. This research builds on the availability of remote-sensing data for the social sciences. The chapter argued that studying the temperature impacts on maternal and infant health is relevant to the intersection of environmental and reproductive justice.

Next, Chapter II presents a methodological framework for the linkage of climatic conditions with birth records on the micro-level. It discusses key issues relating to data sources, measurement construction, and statistical modelling. The focus lies on the linkage of DHS and high-resolution, gridded temperature data to inform the empirical work of this thesis.

The following three chapters provide innovative empirical applications of this methodological framework. Chapter III investigates a health-related behavioural response to extreme heat. It analyzes the impact of gestational temperature exposure on antenatal care visits with DHS data from 52 countries. The aim of this chapter is to uncover inequities between world regions, countries, and social groups in the impact of extreme heat on maternal healthcare access.

Chapter IV studies the effect of gestational temperature exposure on the SRB in a comparative perspective between Sub-Saharan Africa and India. In these settings, I test two mechanisms that could explain heat-induced reductions in male births. I focus on a socio-behavioural mechanism – changes in sex-selective abortions of girls under heat – and a physiological health mechanism – heat-induced pregnancy loss.

Chapter V builds on the finding that prenatal heat exposure can induce pregnancy loss particularly of weaker offspring and asks whether this could lead to a positively selected offspring cohort after birth. The chapter finds that prenatal heat exposure reduces infant mortality. This suggests that intensified prenatal selection dominates the scarring effect of extreme heat. I study this question in Mali, a context characterized by both extreme levels of heat and high infant mortality.

Finally, Chapter VI concludes this thesis by synthesizing the findings and limitations across the empirical chapters, reflecting on ethical and practical considerations for climate-health research in the context of the DHS Program's termination in 2025, and highlighting key directions for future research.

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Chapter II: Data, measurement, and modelling issues for temperature-birth linkages

Methodological chapter

Co-authorship note: This chapter is based on solo-authored work. No co-authorship contributions to declare.

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Chapter II: Data, measurement, and modelling issues for temperature-birth linkages

Chapter II lays out a comprehensive methodological framework for linking temperature for the in-utero period with birth records, with specific application to high-resolution, gridded environmental data and birth histories from the DHS. This framework responds to the variety of methodological approaches applied in the literature on temperature impacts on reproductive and infant health, which have, at times, led to contradictory findings, even with the same population data source and in the same study area (Barreca et al., 2018; Conte Keivabu et al., 2024; Gray & Thiede, 2024; Thiede et al., 2022). The methodological framework I present is founded in emerging empirical evidence, theoretical arguments, and triangulation from the empirical chapters in this thesis. I rigorously apply this framework in the following empirical chapters to demonstrate how it can advance our understanding of climate change impacts on a range of maternal and infant health outcomes across a diverse range of contexts.

This chapter on data, measurement, and modelling issues for temperature-birth linkages makes several contributions. First, after introducing the data sources used in this thesis, I provide a novel framework that defines spatial and temporal coverage, spatial and temporal resolution, and validity as fundamental criteria that guide the choice of data sources (section 1). In this context, I provide an accessible introduction to high-resolution, gridded environmental data. I critically evaluate characteristics of gridded data compared to time series data with application in mind, promoting the use of gridded data to improve causal identification.

Second, this chapter lays out the process of linking gridded environmental data with birth records from the DHS (section 2). In LMICs, data sources often do not report gestational duration, but I explain a consistent approach to estimating the gestational or prenatal exposure period for each individual birth record. Further, I define clear criteria based on which the environmental data extraction is undertaken to force the micro-level linkage: Temporal bounds (the exposure period of each birth) and spatial bounds (the georeferenced location of the mother during pregnancy). In this chapter, I also address a multitude of measurement issues that have led to inconsistent methodological approaches in the literature. I offer a way forward by arguing that the use of absolute temperature bins has many advantages over other measurement types in the context of climate-birth linkages.

In section 3 of this chapter, I present a causal identification strategy that uses place-time fixed effects. This strategy has been applied in climate econometrics and demography. My contribution here is to provide a detailed explanation of its application that is specific to temperature as the exposure and reproductive and infant health outcomes. In addition, I evaluate different sources of omitted variables bias and conceptualize the role of parental characteristics as effect moderators.

1 Population and environmental data

1.1 Overview of population and environment data sources used

Identifying temperature impacts on reproductive health outcomes requires information on 1) the reproductive health outcomes, ideally on the micro-level, and 2) the environmental exposures, ideally at a fine temporal and spatial resolution. The empirical chapters of this thesis draw on birth histories from the Demographic and Health Surveys (DHS) and on temperature and precipitation records from the National Oceanic and Atmospheric Administration (NOAA) and the European Copernicus Agency’s ERA5-Land datasets.

In the following, I will characterize these data sources and demonstrate their advantages for climate-reproductive health analyses in the context of my empirical chapters, describing the DHS as a uniquely rich data source. Next, I conceptualize how five criteria guide the choice of suitable data sources: spatial coverage, spatial resolution, temporal coverage, temporal resolution, and validity. Based on these criteria, I critically evaluate differences between gridded and time series environmental data. In this subchapter, I argue that gridded environmental data offers valid daily estimates of climatic conditions for LMIC populations at the location of each recorded pregnancy in the DHS.

1.1.1 Georeferenced birth histories from the Demographic and Health Surveys

For the empirical chapters I use live birth histories from the DHS. These surveys allow me to examine the effect of temperature on ANC visits (Chapter III), SRBs (Chapter IV), and infant mortality (Chapter V). For each live birth in the sample, I observe the birth sex, the number of antenatal visits the mother had for the pregnancy, and whether the infant died before reaching its first birthday. The DHS Birth Recode files hold information on all live births (used for the analysis on sex ratios), while the Child Recode files hold information on all live births in the five years prior to the interview alongside more detailed information for each child (such as ANC). The data for the empirical chapters were obtained through an access request for research purposes approved by the DHS Program based on project descriptions for each individual study. The DHS Program was terminated in January 2025, resulting in no new approvals for access requests. While my empirical studies were unaffected by the sudden termination, I reflect on the implications of this data infrastructure change in the conclusion chapter of this thesis (Chapter VI).

The DHS Program has produced more than 400 cross-sectional surveys in more than 60 LMICs since 1984. The DHS are cross-sectional household surveys of reproductive-aged women whose full birth histories are recorded. DHS uses a two-stage sampling where enumeration areas are drawn from census files (first stage) and a sample of households is drawn from an updated list of households in each enumeration area (second stage). This makes the surveys generally representative at the national level, the residence level (urban/rural), and the subnational regional level (first administrative unit) (The DHS Program, n.d.-a). The Woman's Questionnaire, the Man's Questionnaire, and the Household Questionnaire cover topics on fertility, maternal health, family planning, sexual and reproductive health, child health, immunization, mortality, HIV/AIDS, malaria, nutrition, household characteristics, socioeconomic conditions, female empowerment, and more. The downloadable surveys include Birth Recode, Child Recode, Household Recode, and Partner Recode files. The Birth Recode files have one record for every child ever born to the interviewed woman – these are full birth histories that I use for the analysis on SRBs. The Child Recode files have one record for every child born to the interviewed woman in the five years prior to the interview. While these are not full birth histories, they offer detailed information on each child, including on infant mortality and ANC. Hence, my empirical Chapters III and V on these outcomes are based on Child Recode files.

For studies on climate impacts on fertility, maternal health, and child health in LMICs, the DHS have become a widely used data source (Andriano, 2023; Cooper et al., 2021; Dimitrova et al., 2022) because of several important characteristics that enable data linkage. Alternative data sources include the Health and Demographic Surveillance Systems (HDSS), census microdata files, UNICEF's Multiple Indicator Cluster Surveys (MICS), the Young Lives Study, the Living Standards and Measurement Surveys Integrated Surveys on Agriculture (LSMS-ISA), and countless national data collections. However, as explained in the following, the DHS are a unique data source for climate-birth linkages in LMICs because they combine crucial properties for climate-health research in LMICs: DHS offer a) micro-level data on births, b) alongside sociodemographic characteristics of the mother and household, c) which are georeferenced to allow for environmental linkage, d) harmonized across a large set of countries, and e) generally of high quality and f) (sub-)nationally representative.

Firstly, the recent DHS surveys are georeferenced at the Primary Sampling Unit (cluster). The cluster refers to a group of households that usually corresponds to a village or a city block. For these clusters, latitude and longitude information is recorded either with a GPS unit or approximated with a map or gazetteer. In a spatial format, the cluster's geolocation can be transformed into a spatial point. Using this spatial point, data on environmental conditions at each cluster can be extracted. In the absence of geolocation information, environmental data would need to be aggregated to the closest unit on which information is available (such as country, subnational region, district of residence of the respondent), which reduces spatial variation in the exposure measurement. Because DHS are nationally representative, they cover clusters across different geographic areas within each country. This means there is substantial spatial variation in the exposure that can be exploited for causal inference. This design is a major advantage of the DHS over the Health and Demographic Surveillance Systems (HDSS) that are limited to 29 sites where respondents are followed longitudinally.

Secondly, the DHS offers micro-level records of births rather than population level aggregates over a time period. For each birth, month and year of birth are recorded, and in newer surveys the day of birth and gestational length in months, too. Using birth date information, the mother's pregnancy period can be approximated. This then allows a linkage of environmental conditions with each individual birth's *in-utero* period. Compared to earlier correlational studies that used annual, country level birth and temperature records (Catalano et al., 2008; Helle et al., 2008), micro-level linkages can aid causal inference more plausibly by attributing the exposure to an individual's life-course.

Third, the DHS provides detailed information on the sociodemographic characteristics of mothers and some household and community level characteristics. These include maternal age and education, the mother's partner's education, rural/urban residence, land ownership, household amenities, and more. This information is critical for identifying subgroups of the population that are most vulnerable to the impacts of extreme heat. It also helps to identify individual and community level factors that aid individuals and households in resilience and recovery from the exposure. Lastly, sociodemographic information can illuminate mechanisms that explain how the exposure is linked to the outcome.

Fourth, the DHS fill an important gap in the data landscape on LMICs, providing harmonized high-quality data across countries. Cross-national data can help us understand underlying mechanisms better by uncovering how the exposure causes variation in the outcome in different contexts. As countries have differing characteristics in their population structures, climatic and weather conditions, and social, economic, cultural, and political factors, comparisons between countries can be exploited to work out differential responses to the environmental stressor. Cross-national analyses can also highlight inequities between countries and point us to contexts where populations are disproportionately affected by climatic stressors. Lastly, from a statistical perspective, data from several countries can ensure sufficient sample size for effect identification by pooling several surveys into one analysis sample.[4] The DHS Program also provides detailed and reliable data documentation for users.[5]

1.1.2 High-resolution, gridded environmental data from NOAA and ERA5-Land

My empirical chapters draw on temperature records as the main exposure and rainfall records for controls from two data sources: the National Oceanic and Atmospheric Administration's (NOAA) Global Unified Temperature dataset and the European Copernicus Agency's ERA5-Land dataset. These data sources are reanalysis products that have global geographic coverage since 1979 (NOAA) and 1950 (ERA5-Land) to now. Both data sources provide gridded temperature and rainfall data on a fine temporal and spatial resolution. The NOAA data (used for the sex ratio Chapter IV) provides daily temperature and rainfall values at a resolution of 0.5×0.5 degrees (ca. 55.5km^2 around the equator). The ERA5-Land data (used for the ANC and infant mortality Chapters III and V) provides hourly temperature and rainfall values at a resolution of 0.1×0.1 degrees (ca. 9km^2 around the equator).

1.2 Choosing environmental data for the analysis

To exploit temperature variation that could induce changes in the outcome under study, reliable temperature estimates are needed for the geographical area and time period under study. These estimates need to be at a spatial and temporal resolution that allows

[4] However, this can be a trade-off with preserving heterogeneity by not pooling samples.
[5] Censuses micro data files and vital registration records, such as those available through IPUMS (https://international.ipums.org/international/), can be an alternative data source on LMICs that offer large sample size, but data quality differs across countries.

for sensible inference. The suitability of environmental datasets for identifying temperature impacts on reproductive health outcomes ultimately depends on five main criteria: Spatial and temporal coverage, spatial and temporal resolution, and validity **(Table 1**).

Table 1: Five main criteria for suitability of environmental data products for climate-reproductive health linkages

Spatial coverage	The geographical area covered
Temporal coverage	The time period covered
Spatial resolution	Values on the country level, subnational level, grid with resolution of x degrees, etc.
Temporal resolution	Hourly, daily, monthly, annually, seasonally
Validity	The validity of the data source's estimates for the variables of interest

1.2.1 Spatial and temporal coverage: Fundamental for linkage

The first two criteria, *spatial and temporal coverage*, ensure that information on environmental conditions is available at the geographic location where individuals were exposed at the exposure time of interest in their life-courses. For example, for an analysis on in-utero temperature impacts information is required on temperature at the location where the infant's mother resided during pregnancy (spatial coverage), as marked by the conception and birth date (temporal coverage). As such, the environmental data source ideally covers the coordinates of pregnancy locations of all pregnancies in the sample (spatial coverage), and the earliest conception and latest birth date of the sampled pregnancies (temporal coverage).

While ensuring geographic and temporal coverage seems straightforward in theory, challenges can arise in practice. I describe two examples where ensuring coverage can be challenging when using gridded and weather station data in **Appendix 1**.

1.2.2 Spatial resolution: How fine can you go?

The third criterion, *spatial resolution,* refers to how small the geographic units are for which the environmental data is provided. Gridded temperature data overlays the globe's surface with a layer of grid cells, where each grid cell covers a geographic area. In this context, spatial resolution refers to the size of grid cells, i.e. how large the geographic area is that is covered by a grid cell. Large improvements have been made in increasing spatial resolution for environmental variables globally in recent years. Currently, to my knowledge, the finest spatial resolution for temperature is available through the European Copernicus Agency's ERA5 datasets, which have a 0.05×0.05 resolution. This equals ca. 9 km^2 around the equator (and even less moving north/south because of the convergence of meridians toward the poles). CHIRTS also offers a very high resolution of 0.1×0.1 degrees (ca. 11.1km^2 around the equator) but has temporal coverage only until 2016.

For explanation on spatial resolution in time series or weather station data, please refer to **Appendix 2**.

1.2.3 Temporal resolution: Measurement frequency

Fourth, *temporal resolution* refers to how frequently measurements are provided for each geographic unit, e.g., hourly, daily, annually, or once per season. Daily country level data would provide 365/366 daily measurements per year for each country. Hourly data requires large storage capacity. But it allows researchers to compute the daily minimum, maximum, and mean of temperature data. It additionally allows researchers to compute daylight and nighttime temperature. Daily data is usually provided as the daily minimum, maximum, and mean value. Unlike annual temperature records, daily temperature records allow for very flexible measurement construction and enable mapping of the exposure duration exactly onto the estimated gestational duration (i.e., a micro-level linkage can be undertaken, which aids causal inference, see section 2).

The dataset's temporal resolution is not to be confused with its "update frequency". The update frequency indicates how often the measurements for the last time point will be provided on the platform to the user.[6]

1.2.4 Validity of data products

Fifth, the data products used are ideally validated, meaning the accuracy of the provided estimates was tested. In validation studies, estimates from the data product of interest are compared against a different data source, such as weather station data. For example, comparative analyses found that ERA5 products generally compare well to station measurements but can underestimate heat extremes in the context of temperature-related mortality in tropical regions (Mistry et al., 2022). In my empirical studies, I have used ERA5-Land nevertheless due to its temporal coverage and high spatial resolution. NOAA has been found to reflect well a global warming trend (Hausfather et al., 2016). Although this chapter cannot outline the methodological approach of validation studies in detail, data users are encouraged to confirm that the data products for their analyses provide valid estimates of their variables of interest.

1.3 Comparison of gridded and time series environmental data

Gridded and time series environmental datasets typically differ in terms of their coverage and resolution. In the following, I describe how gridded environmental data is structured and explain the (dis)advantages of both data types. I argue that gridded environmental data provides higher spatial and temporal resolution as well as flexibility in exposure measurement construction. For these reasons, I use gridded environmental data in all my empirical chapters.

1.3.1 Characteristics of high-resolution, gridded environmental data

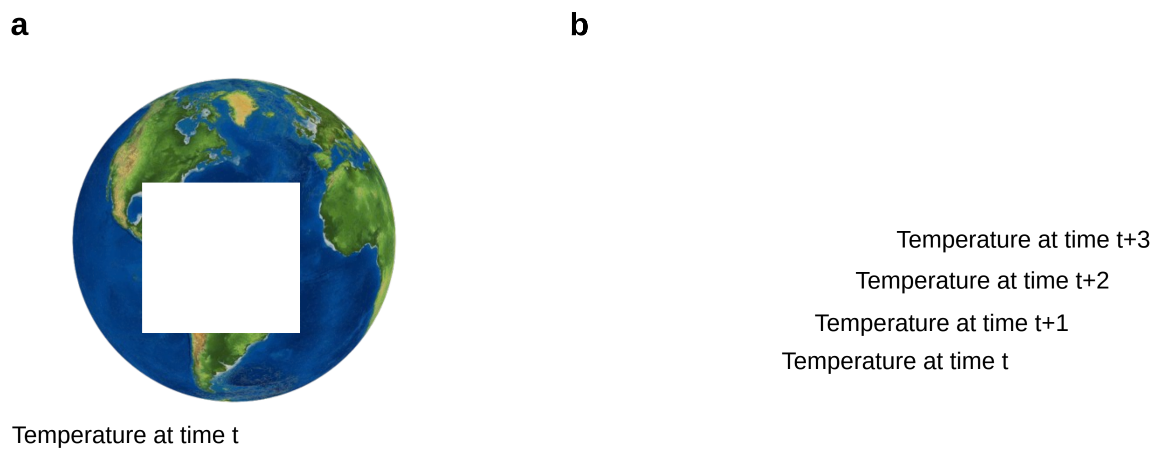
Gridded environmental datasets are reanalysis products that use in-situ observations from a range of devices. ERA5-Land is based on in-situ observations from satellites, land

[6] For example, for the European Copernicus Agency's ERA5 daily datasets are updated daily, meaning that the measurements for the next day in the series are provided daily – rather than the user needing to wait until the next year for the data of the concurrent year to become available.

stations, drifting buoys, radars, radiosondes, aircraft data, and more (Hersbach et al., 2020; Muñoz-Sabater et al., 2021). In the reanalysis process, values for each grid cell (i.e. for each geographic area) are computed drawing on observations from these data sources. The availability of global, *high-resolution, gridded data* on environmental variables has led to a revolution in social research, allowing the linkage of health and social outcomes on the individual and population level with detailed records of environmental conditions at the location of individuals (National Research Council, 1998). Many recent studies in climate demography rely on high-resolution, gridded data due to their increased availability and many advantages over time series station data, as outlined below.

To explain how gridded data is structured, gridded datasets can be visualized as a series of small chessboards that are overlaid onto the globe's surface. **Figure 1a** provides a very crude visualization. In fact, the size of grid cells is significantly smaller (e.g. ca. 9 km^2 around the equator) than depicted and the earth's surface and coordinate systems give grid cells varying sizes at different latitudes. Each grid cell holds a temperature value at time t, which can differ from the other grid cells. As pixels become smaller, the spatial resolution becomes finer as a smaller geographic area is covered by each grid cell. This means that a dataset of higher resolution can provide more variation in temperature values for the same geographic area. To visualize the temporal structure of gridded datasets, they can be compared to a stack of chessboards on top of each other, where each layer represents one time point (**Figure 1b**). If the gridded dataset has an hourly temporal resolution, there is one layer (raster) for each hour. Hence, to extract the environmental data at the mother's residence location for a given pregnancy, the values of the grid cell into which the mother's residence location falls are extracted – across all temporal layers that correspond with any of the days in the pregnancy duration.

Figure 1: Visualization of gridded temperature data across several time points. Source: Own illustration and (Free SVG, 2020).



It should be noted that gridded datasets can be converted from a raster format into a time series format, where each location (or grid cell) is paired with temperature values over time. In Chapter V on infant mortality, I used gridded temperature data, but I extracted the temperature values from all grid cells that intersected with the Primary Sampling Units (clusters, i.e. a village or city block) to then construct a time series of daily temperature values for each cluster. Compared to using time series data where information is only available in the vicinity of weather stations, this approach increased spatial coverage.

1.3.2 Characteristics of time series environmental data

An alternative data format to gridded data on environmental conditions is *time series* data. Time series data indicate one value for each environmental variable at each time point for a constant geographic unit, such as the country or municipality (rather than for grid cells in a raster format).

Some data products present time series data based on an aggregation of gridded environmental data at different levels, such as averages for the country level. For example, the World Bank Climate Change Knowledge Portal provides publicly available annual, monthly, and seasonal data on a range of environmental indicators, including average temperature and number of heat days at different heat intensity thresholds. In other data products, the values for each environmental variable stem directly from weather station observations at each station’s location – unless they were cleaned by the provider. The restriction of these data products to weather stations as the only source of information limits their coverage to these stations’ locations (and adjacent areas if researchers extend inference to these).

1.3.3 Working with gridded vs. time series data

Table 2 provides a comparative overview of key characteristics of gridded and time series environmental data. This section provides insight on the most important issues that guide the choice between gridded and time series data for climate-birth linkages. It should be noted that a wealth of data sources with differing characteristics exists, and other publicly available datasets might differ from the specific characterization presented here.

Gridded data overcome many existing issues of time series data, which rely on weather station observations. Firstly, they extend geographic coverage often to a global grid. They improve upon the missingness of observations due to a lack of station coverage, particularly in LMICs. But they also improve upon the unequal station distribution and density that can lead to bias in analysis estimates because of non-randomness. Secondly, many reanalysis products offer both high spatial *and* high temporal resolution. This allows researchers to attribute exposure conditions at a fine spatial resolution to individuals, and to flexibly compute their own exposure measurements using hourly or daily temperature records.

Gridded data requires significantly more space to store and computational power to process than time series data. This can be challenging particularly for cross-national analyses. When merging gridded data with household survey data, usually only information on environmental conditions at the household location is necessary. But before the information can be extracted for only the relevant grid cells where the households are located, data for the entire geographic area that falls between the coordinates of the outermost households first needs to be downloaded and stored. After the download, the raster data for these large geographic areas can then be masked around the specific cluster or household locations, which significantly reduces their size. Alternatively, they can also be aggregated, e.g., to a single country level or subnational regional measurement for each time point.

As an example, I faced data storage issues working on Chapter III, an analysis of temperature impacts on antenatal visits. For this study, I downloaded gridded temperature and rainfall data across 52 countries for around 96,000 cluster locations at an hourly temporal resolution and a spatial resolution of 0.1 degrees. The downloaded data required 950 GB of storage space and further space was necessary to process the data. This example highlights how important data infrastructures are to conduct high quality environmental-health research that covers large geographic areas. The infrastructure challenges associated with storing and processing large raster data are also a source of inequity in this field of research, with researchers based at LMIC institutions being underrepresented.

By contrast, the main advantage of time series data over gridded data products lies in their ease of use. Environmental data in time series format are often publicly available, faster to download, and require significantly less storage space and data wrangling than gridded data. They can be linked to survey data using a region identifier. Typically, time series environmental data holds significantly fewer values for the same geographic area than gridded data, because values are often aggregated to a spatial unit (e.g., a country) already. But even when no aggregation has taken place, over the same geographic area the number of grid cells from modern high-resolution datasets usually exceeds the number of weather stations[7]. **Table 2** highlights two examples. The World Bank Climate Change Knowledge Portal provides aggregated data on the country level, and – for a much smaller subset of countries – on the subnational state level. The Global Historical Climatology Network provides temperature data from weather stations across the globe, but station distribution varies significantly (Ortiz-Bobea, 2021).

[7] Though this depends on the spatial resolution of the gridded data.

However, time series products usually have several limitations. First, many data providers only offer a limited set of variables. The available variables may not always fit the theoretical assumptions about pathways that link temperature and the outcome and can be incompatible with the identification strategy chosen. Second, time series data can lack necessary temporal resolution levels. For example, the identification strategy I employ in all my empirical chapters is based on count variables that indicate the number of days within a 5°C temperature range during gestation. This requires *daily* temperature records, which are not always available in time series data products. Furthermore, time series datasets have a much coarser spatial resolution than state-of-the-art gridded data products. As mentioned, time series values are usually on the weather station, municipality, country, or sometimes on the first subnational administrative level (e.g., states). Linking individuals' residence locations at larger geographic entities makes strong assumptions that the individuals were indeed exposed to the temperature conditions recorded as the state or country's average[8]. In other words, time series data often force linkages with population records that ignore substantial subnational heterogeneity in temperature variation. This also significantly limits the temperature variation in the sample, from which the effect can be identified off – because all individuals in the same geographical unit are assigned the same exposure value at time t.

Table 2: Typical characteristics of gridded and time series environmental data

Characteristics	**Gridded data**	**Time series data**
Geographic coverage	Typically, available globally or at the country level	Varied, from local weather station data to global coverage
Temporal coverage	Varied, readily available for historical time periods, recent years, and future time periods	Varied, often dependent on weather station introduction
Spatial resolution	Fine resolution: Often 0.5×0.5 degrees (ca. 55.5km^2 around the equator) or higher, recently up to	Typically, coarser resolution or distribution issues: Weather station data can have issues around

[8] The same applies for weather station data, where a common approach is to attribute temperature values from the nearest station to the individual. I explain this in more detail earlier in the section on "Spatial and temporal coverage: Fundamental for linkage".

	0.05×0.05 degrees (ca. 9km^2 around the equator)	spatial distribution and coverage, while data aggregated to the municipality, state, or country level have less fine resolution than gridded data
Temporal resolution	Fine resolution available: Often available annually, daily, but also hourly, allowing for flexibility	Typically, coarser resolution: Daily, monthly, or annually (though weather station data is also available hourly)
Examples and availability	ERA5: Publicly available at the Copernicus Climate Data Store (https://cds.climate.copernicus.eu), access is requested through ECMWF and API download is available CHIRTS: Publicly available at https://www.chc.ucsb.edu/data NOAA: Publicly available at https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html	Data Catalogue of the World Bank Climate Change Knowledge Portal: Publicly available at https://climateknowledgeportal.worldbank.org/download-data Global Historical Climatology Network: Publicly available at https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily (monthly data also available)

In summary, while time series data is easier to use, its spatial coverage, spatial, and temporal resolution tend to be more limited, which can limit flexibility in constructing exposure measurements later. This ultimately has implications for the way temperature impacts can be modelled. Relying on weather station data can force researchers to make strong assumptions about individual level exposure, by attributing exposure at larger geographical entities or less proximate stations to the individual. These reasons have motivated the use of gridded environmental data in my empirical chapters.

1.4 Summary

The empirical chapters of this thesis utilize birth histories from the DHS. The DHS offer micro-level data on births, alongside sociodemographic characteristics of the mother and household, are georeferenced to allow for environmental linkage, harmonized across a large set of countries, and generally of high quality and (sub-)nationally representative. I link these DHS birth histories with high-resolution, gridded temperature data from NOAA and ERA5. These gridded data products have advantages over alternative time series data sources because of their extensive temporal and spatial coverage and resolution. Their characteristics allow for more accurate linkage of climatic conditions with critical periods in individual's life-courses. They also increase variation in the temperature exposure measurement needed to identify temperature impacts on the outcomes of interest.

2 Exposure measurements and data linkage

This subchapter outlines the process of constructing measurements of prenatal (or gestational) temperature exposure. The georeferenced DHS's detailed live birth histories enable a *micro-level linkage* of environmental conditions with each individual birth record. From a practical perspective, there are two types of information that are necessary for this micro-level linkage: (1) The temporal information for each birth, which defines the gestational period individually for each birth, as outlined in section 2.1. (2) Spatial information for each birth is necessary, which in the DHS comes from the cluster location, which defines the geographic area for which temperature data is extracted. Once each birth's exposure period and geolocation are defined, environmental data can be extracted for the exposure period at the location where the pregnancy is assumed to have taken place. In the following, I outline these steps and offer considerations that need to be made at each stage of the measurement construction process.

In the final analysis sample, there will be two sources of variation in the temperature exposure: Differences in (1) the location of the birth and (2) the timing of the birth. If gestational length information is available, variation can additionally be induced by differences in (3) gestational length. This means that for pregnancies where gestation takes place at the same location, and birth takes place on the same date, and the (assumed or observed) gestational length is the same, the exposure variables take the same values because gestation takes place at the same location and time.

2.1 Defining the exposure period of interest for each birth

To link individual birth records with environmental exposures, the critical exposure period across the mother's or infant's life-course needs to be identified. For example, if the interest lies in identifying the impact of temperature in the prenatal period on an outcome, the exposure period of primary interest is the in-utero period. The micro-level linkages applied in the empirical chapters of this thesis imply that the exposure period is defined for each birth individually (as one record exists for each birth).

2.1.1 Exposure during gestation or in the prenatal period

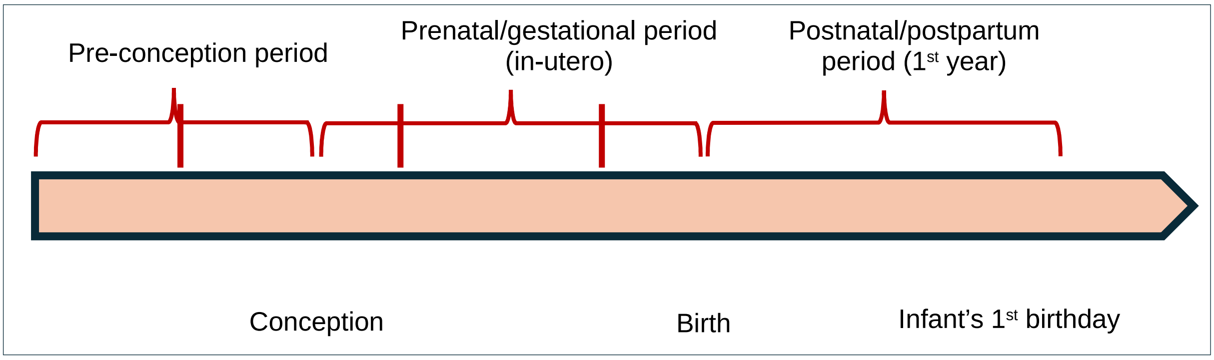
To define critical and sensitive exposure periods, Grace et al. (2020) have provided a framework that introduces epidemiological concepts of exposure science to the study of environmental impacts on reproductive and infant health. The epidemiological literature (Kuh & Ben Shlomo, 2004) discusses critical periods as time windows in the individual's life-course, where exposure could affect the outcome. In sensitive periods this effect is especially strong.

In the case of climate-birth linkages, the critical exposure period of primary interest is usually the prenatal or gestational period[9]. For live births, the gestational period is marked by conception as the start date and birth as the end date (**Figure 2**). Gestational exposure variables can capture temperature variation that occurs in (1) gestation, or alternatively in (2) each gestational trimester, (3) each gestational month, or (4) each gestational week.

[9] This thesis refers to this time window as the "prenatal" period when examining outcomes of infants after they were prenatally exposed (e.g. in Chapter V on the effect of prenatal heat exposure on infant mortality). Alternatively, I refer to the time window as the "gestational" period when maternal health outcomes (e.g. ANC visits in Chapter III) are examined and in Chapter IV on SRBs. In this chapter, for simplification, I use the term "gestational" period – but the same issues apply to the identification of prenatal temperature impacts.

When using the entire pregnancy period, the temperature exposure measurements capture temperature variation in the entire gestational period. Alternatively, when using gestational trimesters, exposure variables are constructed for each individual trimester. A single pregnancy exposure measurement can be useful for example when statistical power needs to be preserved by limiting the number of regressors. This approach makes few assumptions about which time windows in gestation are relevant when the exposure affects the outcome. Conversely, such measurements also cannot provide insight into this question.

Figure 2: Pre-conception, gestational, and postnatal exposure periods



In the literature on temperature and fertility and maternal health, a range of exposure periods have been used to cover the gestational period. Earlier studies used annual exposure measurements (Catalano et al., 2008; Helle et al., 2008). The literature has since rapidly evolved, and this approach is now less common. The drawback here is that most gestations extend over two calendar years. By contrast, some recent studies use exposure across gestational weeks, such as Barreca et al.'s study (2018) on temperature impacts on birth rates using US Vital Statistics. Splitting the gestational period into several exposure periods provides insight into which window of pregnancy is (most) sensitive to the exposure. It can also aid mechanisms identification (as demonstrated in Chapter IV on SRBs) and be helpful in identifying effective interventions. However, using weekly exposure measurements is only feasible and meaningful when reliable information on birth dates, and gestational length or estimated conception dates are available.

In my empirical chapters on SRBs (IV) and infant mortality (V), I use trimester exposure measurements. In the chapter on ANC visits (III), I use measurements for the entire gestational period because here, extreme heat could lead to postponement of ANC visits that then impacts the number of visits in subsequent gestational time windows.

2.1.2 Exposure during the (pre-)conception window

Researchers may additionally be interested in how environmental exposures during conception or even before conception affect outcomes at birth and after birth. Pregnancy outcomes are not only shaped by maternal health conditions during *gestation* but also by maternal and paternal health conditions before and during *conception*. For example, for heat exposure in the two weeks before conception, Barreca et al. (2018) observe a decline in birth rates. Heat exposure has also been linked to lower sperm quality and quantity in humans (Boni, 2019; Hoang-Thi et al., 2022) and other mammals (Hansen, 2009). However, maternal and paternal environmental exposures are usually extremely difficult to disentangle (see further explanations in **Appendix 3**).

The pre-conception period is sometimes also included in models to control for the autocorrelation of time lags and for robustness checks that aim to demonstrate that only in-utero exposure affects the outcome, but not pre-conception exposure (e.g. Andriano, 2023). How many time lags should be included to control for autocorrelation? This depends on how fine the temporal frequency of the exposure variables is. When using gestational exposure months, up to 11 monthly lags of the birth month should be included to avoid inducing additional autocorrelation from even earlier lags (temperature in January of year y and January of year y-t are usually highly correlated).

In Chapter IV, I include a supplemental analysis using monthly lags that capture the pre-conception period but find no effects of the pre-conception temperature on the sex ratio at birth.

2.1.3 Estimating the gestational window

Identifying the gestational period accurately is an important concern in climate-reproductive health studies. Gestational lengths can vary significantly, particularly in LMICs where preterm births affect a significant proportion of live births. Preterm birth is defined as live birth before 37 weeks of gestation are completed (WHO, 2023). Blencowe et al. (2012) estimated that 7.2–13.6% of live births in Millennium Development Goal countries in 1990-2010 were born preterm. For Sub-Saharan Africa, their estimate lies at 12.3 % and more recent studies estimate the share at 10.1 % (Ohuma et al., 2023). Births with differing gestational lengths are ideally assigned differing temperature exposure values to avoid exposure misclassification, as the variation in environmental conditions would be reflected more accurately.

Ideally, information on the birth and conception dates (i.e. the start and end dates of gestation) allows researchers to clearly identify for each birth for which dates environmental data should be extracted – but this information is not always available. In the majority of DHS surveys, only month of birth information is available. This forces researchers to use the month of birth as the end point of pregnancy and include eight to nine monthly lags to approximate the gestational period. I use this approach in Chapter IV on sex ratios, where I collapse the monthly lags into approximate trimesters. In Chapter III on ANC visits, I collapse the monthly lags into one entire pregnancy period. In Chapter IV, I assign the first 12 weeks of the gestational period to the first trimester, 14 weeks to the second trimester, and the remainder of the gestational period to the third trimester. An alternative approach would be to limit the sample to births from DHS surveys where day of birth information is available. I do not choose this approach as it would have significantly reduced the coverage of countries and the sample size necessary, especially for heterogeneity analyses.

There are two issues associated with assuming a standard duration of nine to ten months (or 40 weeks) of pregnancy for all births in the analysis sample. Firstly, for births with shorter gestational lengths the constructed exposure period of nine months will include pre-conception exposure, conflating the in-utero period with exposure before conception has occurred. Secondly, if researchers construct trimester exposures, the demarcation of trimester dates will be off for shorter pregnancies, leading to a conflation of gestational timings in the treatment variable (e.g., for a preterm birth occurring in the second gestational trimester, the temperature values that technically fall into the second trimester will at least partially be assigned under the third trimester). While these are important caveats, they are likely to lead to an underestimation of the true effect of heat in the prenatal period. Errors in identifying the exposure period for shorter pregnancies should bias the effect identified from standard-length pregnancies towards the null.

In some of the more recent DHS-VII surveys, the DHS records day of birth and gestational length (in months) information. Using this information, researchers can subtract the gestational length from the day of birth to derive an approximate conception date. Trimesters can then be assigned as described above. I use this approach in Chapter V where I strategically chose the Mali 2018 DHS for the analysis because it reports the day of birth and gestational length.

There are two more general challenges to identifying the gestational period reliably using DHS data with the provided day of birth and gestational length information. Firstly, even when day of birth information is available, it is not always accurate. For example, I observed heaping of birth dates in my sample for Chapter V (prenatal heat exposure and infant mortality in Mali), which is in line with studies that examine data quality on infant death reporting (Neal, 2012; The DHS Program, n.d.-b). Secondly, the DHS reports gestational length only in months. This still limits accuracy on the estimated conception date compared to reporting gestational weeks or the date of the last menses. In addition, gestational length may suffer from manifold reporting errors, too (which may not necessarily lead to estimate bias, however). Despite these limitations, the DHS constitutes an important data source on live births in LMICs, particularly for cross-national analyses in data scarce areas.

Once the exposure period is defined for each birth, this sets the temporal bounds for the extraction of environmental data. The data is extracted for each birth for the gestational exposure period at the location where the pregnancy took place. For example, if the gestational period is estimated to have taken place from 1 January 2000 until 7 October 2000 (40 weeks), environmental data is extracted for every date that falls into this period. If date of birth is only reported in months in the population data source, October would be the month of birth (*lag 0*). Temperature data is then extracted for October (the month of birth) and the eight or nine preceding calendar months to cover the gestational period.

2.2 Extracting environmental data for each birth

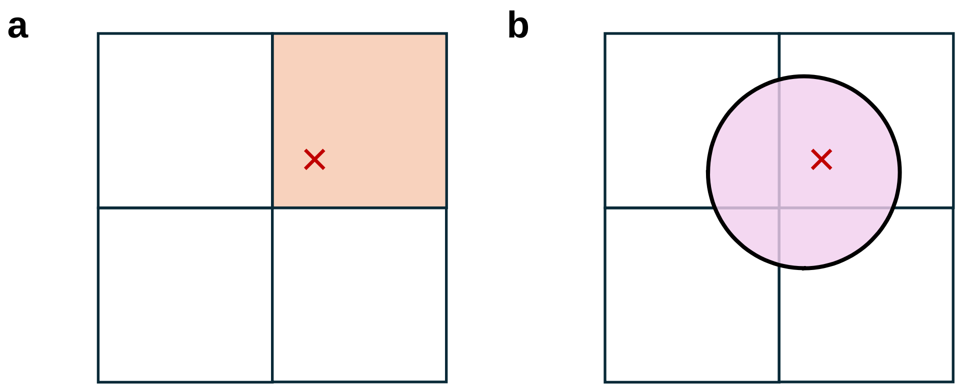
2.2.1 Micro-level linkage of environmental conditions

The spatial bounds of the extraction for each birth are determined by the geoinformation from the population records. In the DHS surveys where GPS information is available, the cluster where the respondent's interview took place is georeferenced. A cluster is the smallest geographical survey statistical unit for DHS surveys and defined as a grouping of households, typically corresponding to a city block in an urban area or a village, part of a village or a group of small villages in a rural area (The DHS Program, 2012). Each cluster's latitude and longitude information are recorded. Overlaying the gridded environmental dataset (i.e. the chessboards from **Figure 3a**) with the cluster locations, each cluster's latitude and longitude (red cross) point to a unique location on the raster, i.e. they point to a unique grid cell (or chessboard field) of a raster layer. This grid cell (orange shaded in **Figure 3a**) is the one for which environmental data should be extracted for pregnancies that took place at the respective cluster. [10]

[10] If the population data source does not provide a geolocation (latitude, longitude) but instead information on the district, state, or country level, gridded environmental data can be aggregated to these levels. I do not discuss the process of aggregating gridded data to polygons here further because the georeferenced DHS provide information on the cluster's latitude and longitude.

Finally, to undertake the extraction of environmental data for each birth, the temporal and spatial bounds are combined. To summarize, the extraction's spatial bounds are defined by the overlap between clusters and grid cells, whereas the gestational period defines the temporal bounds. More specifically, this means that for a given pregnancy, a) the values of the grid cell into which the mother's cluster falls are extracted b) across all temporal layers that correspond with the gestational days (the stack of chessboards in **Figure 1b**). The result of this extraction would yield a record of daily temperature values (or rainfall or any other variable) for each individual birth record. Next, the exposure variables are constructed by drawing on these location-specific temperature records for each pregnancy. The next section outlines how I constructed exposure variables for the empirical studies of this thesis.

Figure 3: DHS cluster location on a gridded dataset



2.2.2 Handling DHS spatial displacement of clusters

Researchers need to consider that the DHS displaces the true point location of clusters in any random direction by 0-5 km in rural and 0-2 km in urban areas, and a further 1% of rural clusters is randomly displaced by up to 10 km (ICF International, 2013). This displacement is undertaken to preserve anonymity of respondents particularly in areas that are not densely populated. How should researchers handle the displacement? The most common approach is to draw a buffer around the cluster's geolocation by 10km (**Figure 3b**). The buffer intersects with several grid cells. Temperature data can then be extracted for each of the intersecting grid cells. To derive one unique value for each time point (e.g. day) for the cluster, the average of the values of all intersecting grid cells for that time point can be used. Alternatively, a weight can be assigned to each grid cell based on the proportion of the grid cell that intersects with the buffer (purple shaded in **Figure 3b**). This is the approach I use in Chapters III and V.

2.2.3 Migration and mobility: Excluding records with exposure misclassification

Concern arises when the mother did not spend (all) her time during the pregnancy at the recorded cluster location where the interview took place. The DHS does not record the mother's residence location per se, but rather the interview location. When temperature values are assigned to a pregnancy for a location, where the mother did not spend time, this introduces *exposure misclassification error*. Exposure misclassification should usually bias estimates towards the null.

Exposure misclassification error can be minimized in the following ways. The DHS records whether the interview location is the mother's usual residence or whether she is visiting and the number of years the mother has resided at the current location. With this information, researchers can exclude mothers from the analysis sample who were only visitors to the location. In addition, births can be excluded where the mother was not resident at the interview location in the year prior to the year of birth. The exclusion of these records arguably biases the sample towards a group of women who may not be representative of the population, as births by mothers who are internal and international migrants are excluded. However, with the goal of causally identifying the impact of climatic variation on health outcomes in mind, the exclusion of migrants can still be preferable. Unfortunately, due to the lack of migration histories in the DHS, the excluded records cannot be linked with environmental data at a different location other than the reported interview location. In my empirical chapters, I exclude migrants from all my analyses, which changed estimates.

2.3 Defining heat exposure measurements

After temperature records for each sample location are downloaded, exposure measurements can be constructed. Exposure variables capture temperature conditions that indicate temperature intensity at the exposure location for the exposure period.

In the literature on climate impacts on fertility, and reproductive health, many different exposure measurements are used, with no standardized approach. For example, studies on temperature impacts on fertility have used absolute temperature bins in degrees Celsius or Fahrenheit to construct both deviation measurements and temperature bins (Barreca et al., 2018; Conte Keivabu et al., 2024; Thiede et al., 2022).

In the following, I outline the strategy for constructing exposure measurements in my empirical chapters. In all chapters, I use exposure measurements that are 1) based on the daily maximum temperature, 2) the bin method, and 3) absolute values of temperature.

2.3.1 Mean, maximum, or minimum temperature data

Regardless of which type of exposure measurement (see next section) is used in the analysis, a choice needs to be made whether the exposure measurement will be based on mean, maximum, or minimum daily values of the environmental variables. This choice determines which environmental data is downloaded in the previous step. In gridded reanalysis products, temperature data is usually available as the mean, maximum, or minimum hourly (ERA5) or daily (CHIRTS and ERA5) temperature. In Chapters III and V, I download hourly data from ERA5 but then aggregate them into daily values.

The choice between mean, maximum, and minimum temperature will be guided by theoretical arguments about the hypothesized mechanisms at play, existing empirical evidence on which variation is most relevant for the outcome of interest, and ideally, a triangulation for one's own analysis. Since evidence is still emerging and there is no convention in the climate-demography literature (though the use of minimum temperature is rare), triangulation can be particularly useful. I was able to identify heat impacts best in my empirical chapters when using daily maximum temperature.

Different arguments can be made for the use of any of the three values in the context of temperature impacts on reproductive health. Minimum temperature can capture nighttime temperature best. Nighttime temperature could matter because too warm temperatures during the night can disrupt sleep and recovery (Li et al., 2025; Okamoto-Mizuno & Mizuno, 2012). Sexual intercourse might also typically take place in late or early hours of the day in the study population (Refinetti, 2005), rather than during the day when temperature peaks.

By contrast, maximum temperature may be particularly relevant if outdoor temperature exposure occurs during daylight hours. For example, agricultural production activities, physically intensive labor, caretaking activities, and short-distance travels disproportionately take place during the day. Dehydration, which may be linked with heat-induced pregnancy loss (Bonell et al., 2022), is plausibly driven by extreme heat exposure during daylight hours. Additionally, it is likely that fetal strain, which is induced by blood and oxygen diversion away from the placenta to cool the body (ibid.), may already be triggered under shorter episodes of heat exposure during extreme hours of the day. This could explain why in my empirical chapters I could identify heat impacts best with maximum temperature, but I should note that the precise question of whether pregnancy loss probability responds to the number of heat exposure hours in a day has not been empirically investigated yet.

Lastly, mean temperature captures a combination of both nighttime and daytime heat intensity. Cool nighttime temperature could enhance recovery from daylight heat exposure. Therefore, nighttime temperature could moderate some relationships between heat exposure and reproductive health. Conceptually, mean temperature would adjust the maximum daylight heat by the minimum nighttime heat. However, the limitation is just that: If either maximum or minimum temperature drive heat stress, the mean temperature could dilute either effect.

Using mean, maximum, or minimum temperature data the exposure variables can be computed, as described in the next section. For example, when using the bin method with daily maximum temperature, exposure variables are constructed that indicate the number of days in the pregnancy where the daily maximum temperature falls into a specified temperature range.

2.3.2 Types of exposure measurements

There are broadly three alternative types of heat exposure measurements for regression analysis, as summarized in **Table 3**. The temperature exposure measurements capture the temperature conditions in each gestational period (or trimester or month), using the underlying daily temperature values. In the following, I explain the advantages and drawbacks of each measurement type. Based on this discussion, I justify the use of temperature bins in all my empirical chapters.

Table 3: Types of heat exposure measurements

	Summary measurement	**Deviation measurement**	**Temperature bins**
Example	Mean of the daily maximum temperature in each exposure period (e.g., gestation, trimester, month)	Mean of the z-scores of the daily maximum temperature	Count of days where the daily maximum temperature falls into a specified temperature bin range for the exposure period
Calculation	The mean of the daily maximum temperature is defined as $\frac{\sum_{i}^{n} x_i}{n}$ where n is the total number of days in the trimester and	The z-score of the daily maximum temperature for a given day in the trimester is defined as $\frac{x-\mu}{\sigma}$ where x is the daily maximum temperature of the day, μ	The count of days in the trimester on which the daily maximum temperature falls into a specified temperature bin is defined as

	x is the daily maximum temperature	is the mean of the daily maximum temperature in the trimester, and σ is the location-specific historical standard deviation of the daily maximum temperature over typically at least 15 years. The mean z-score for the trimester is the mean of z-scores for the days in the exposure period.	$\sum_{i=1}^{n} I(Min \leq x_i < Max)$ where n is the total number of days in the trimester, Min is the lower bound of the temperature bin and Max is the upper bound of the temperature bin. Usually, several bins are constructed to use several exposure variables at differing heat intensities.

Summary measurements

The first type of exposure measurements relies on a mean value of temperature across the exposure period. For example, this could be the mean of the daily maximum temperature in the gestational period. Summary measurements make data processing less demanding, they are easy to calculate, straight-forward to interpret, and reduce the regression predictors to only one variable for each exposure period. However, they have two important limitations. First, as for all means, the effect of extreme values (extreme heat days or heatwaves) can be obscured. This is a relevant limitation as – although this precise question is understudied – even the presence of only few hot days may already trigger heat stress that impacts fetal survival, based on the biological mechanisms of dehydration and blood and oxygen diversion away from the placenta (Bonell et al., 2022). Hence, the summary measurement can fail to capture some of this important variation that could impact the outcome. Second, summary measurements assume linearity, i.e. the hotter the mean temperature, the stronger the effect on the outcome.

Deviation measurements

Deviation measurements capture how much the daily maximum temperature deviates from usual temperature variations observed in the geographic area. They are computed as the mean of the z-scores for each day, divided by the standard deviation of the location-specific historic reference distribution of temperature over at least 15 years. The denominator can be based on reference distribution of the country, subnational region, or cluster. Deviation measurements hence capture how *extreme* (whether hot or cold) temperatures were in the exposure period, relative to how much they usually vary at the location. While the deviation measurement is an improvement over the summary measurement, it still has crucial limitations. Similarly to the summary measurement, it cannot capture non-linearity. Like the summary measurement, the deviation measurement assumes linearity – but in both directions, i.e. the more extreme the temperature, the larger the effect on the outcome. This also implies this measurement type would prevent me from identifying impacts of temperature intensities in the middle range of the temperature distribution.

Temperature bins

I use a third measurement type – temperature bin variables – to operationalize temperature exposure in all my empirical chapters. This method has been established as the best-practice methodology in the econometrics literature. In the climate econometrics literature, the method has been applied for over a decade because of its advantages in accounting for non-linearity in the effect of temperature (Dell et al., 2014), as opposed to the summary and deviation measurements. The exposure variables are constructed as count variables that indicate the number of days in the exposure period where the daily maximum temperature falls into a specified temperature range (bin). To define cut-offs for each bin, I use 5°C increments. Please see (Dell et al., 2014) for a review of this approach and Barreca et al. (2018) for the first application on temperature impacts on births.

The bin exposure variables in my empirical chapters are constructed in several steps. First, the temperature distribution is divided into several bins that are defined by incremental thresholds. To arrive at the temperature bins for the regressions, I considered the whole continuous distribution of absolute temperatures in degrees Celsius in my samples from below 0°C to more than 35°C. I then divide the distribution into several 5°C bins for each exposure period (<5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, 25–30°C, 30–35°C, >35°C)[11]. The bins are constructed for each exposure period used in the regression (e.g., if the regression uses gestational trimesters then there will be eight bins for each of the three trimesters, hence a total of 24 regressors, similar to Chapter IV on SRBs). Lastly, the exposure variables indicate the count of days in the exposure period where the daily (maximum) temperature falls into the bin range.

The first advantage of bins is that the interpretation of the effect estimates for bins is intuitive. One reference bin is excluded from the regression specification. Hence, effect estimates are interpreted as relative to the reference bin. As an example, in my work on sex ratios (Chapter IV), I exclude the 15-20°C bin for all trimesters. I choose this reference bin because 15-20°C corresponds to a human thermal comfort zone where heat stress should be minimal, as indicated by existing literature (Conte Keivabu et al., 2024). Therefore, the regression coefficient for each bin indicates the effect of one additional day in the exposure period where the daily maximum temperature falls into the specified bin, relative to if the day had been a 15-20°C day. Arguably, assessing the effect of one additional heat day is more intuitive than the result from summary or deviation measurements[12]. Bin estimates can also be used in scientific projections of the outcome

[11] However, in my samples there are very few observations for days below 10°C and above 35°C. Consequently, the estimates for these bins had very large standard errors. For this reason, in Chapter IV on sex ratios I collapsed the <15°C and >30°C bins. In Chapter III on ANC, I collapsed the <10°C bins. Collapsing allowed me to arrive at meaningful estimates, while preserving different levels of the temperature distribution with both cold and hot temperatures in a non-parametric approach.

[12] For the mean measurement for the gestational period, the coefficient would instead indicate the effect of a 1°C increase of temperature in the whole gestational period. It is difficult to imagine how temperatures would need to vary over a nine month period to raise the mean by 1°C.

under climate change, paving the way for future studies. Furthermore, the magnitude of effects can be illustrated, taking the sample's temperature distribution into account. In my empirical studies, I translate the effect of one additional day into the effect of a one-standard deviation increase in exposure days in the sample.

Second, the bins provide individual estimates for each heat intensity level, revealing the relationship between temperature and the outcome at different heat intensity levels to indicate relevant temperature thresholds. This is important, as the literature has produced little insight into which levels of heat intensity may be biologically and behaviourally relevant and the relevant thresholds could differ between mechanisms, populations, and time periods. The bin variables can capture the entire distribution of temperature values in the sample, as the entire distribution is split into, for example, 5°C increments. The method hence makes no strong assumptions about breaking points and does not determine ex-ante which range is biologically significant. Admittedly, the use of 5°C increments is arbitrary, and any other cut-offs could be chosen. I nevertheless believe the division into 5°C bins provides an intuitive framework for interpreting temperature effects. 5°C bins also make my results consistent with existing approaches and findings (Barreca et al., 2018; Conte Keivabu et al., 2024; Hajdu & Hajdu, 2020). The crucial point here is that the chosen cut-offs make few assumptions about the biological significance of different thresholds and allow for an investigation of temperature effects across different heat intensities. In short, the intervals were not chosen because of a known biological threshold effect for each bin – rather, they were chosen to *reveal* the temperature ranges at which there are effects. Given that evidence on relevant temperature thresholds is still emerging, my empirical chapters contribute to the literature by allowing insight into the curve of the relationship between temperature and the outcome across different heat intensities.

The third advantage of bins is that they take into account that the effect of temperature could vary at different heat intensity levels. *Non-linearity* is an important concern in temperature-reproductive health relationships. A model that regresses the outcome on the average daily temperature in the gestation would have a major limitation in that it cannot capture that the effect of temperature may be different at different intensities of heat. For example, the effect of a day with a maximum temperature above 35°C (a very hot day) may be different than the effect of a day with a maximum temperature between 20°C and 25°C (a mildly warm day). Similarly, cold temperatures below 10°C may affect the outcome differently.

In summary, with bins the relationship is estimated flexibly. The bin method lets the model reflect that the effect of temperature on the outcome could vary at different levels of heat intensity. I do not assign any functional form to the relationship – be it linear, quadratic or any other polynomial, etc. Each bin receives an individual effect estimate and its magnitude and direction could differ from the next bin. This means the model allows for non-linearity.[13]

My empirical chapters illustrate why the use of the bin method is useful and has significant implications for the theoretical insight we can gain from the results. In my empirical Chapter III on ANC and Chapter IV on SRBs, a major contribution is that the shape of the curve of the temperature-birth sex relationship is revealed. In the sex ratio study, I do not find a linear relationship between temperature intensity and birth sex. Instead, I find a threshold effect where even mildly hot days with temperature above 20°C are associated with fewer male births. The method also uncovers that this sex difference in prenatal mortality remains stable at higher heat intensities. By contrast, in Chapter III, I show that ANC visits decline in Sub-Saharan Africa *only* when temperature is above 35°C. In other world regions, increases in visits are apparent already from 30°C. These findings

[13] For clarity, I note that the effect *within* each bin is, however, estimated linearly. I use a linear probability model (LPM) as the special case of the ordinary least squares regression (OLS) for binary outcomes. The model assumes that the more days there are in a certain bin, the larger the effect on the outcome. But the model is specified in a way that accounts for non-linearity in the temperature-birth relationship by using bins.

underline that the bin method can point to the temperature thresholds that are in fact biologically and behaviourally relevant, and that the breaking points can be both (1) outcome-specific and (2) context-specific. Given that these breaking points were not established in the literature so far for SRBs nor for ANC, the use of this method enables novel theoretical contributions.

2.3.3 Absolute vs. relative temperature bins

When using the bin method, a further distinction exists between approaches using absolute and relative temperature values to define the cut-off points. In the following, I justify the use of absolute temperature bins in all my empirical chapters. Cut-offs using absolute temperature are based on observed values of temperature in degrees Celsius or Fahrenheit drawn directly from the reanalysis datasets. All above examples use absolute temperature.

By contrast, relative temperature cut-offs define thresholds based on the long-term distribution of temperature at each location. First, temperature data for a long-term distribution of at least 15 years is downloaded for each DHS cluster, or alternatively the country or subnational region. Which period should serve as the reference period is a fairly arbitrary decision. Studies often exclude years before 1980, after which a stark increase in temperature globally because of global warming occurred. Based on the long-term temperature distribution for each location, location-specific percentiles are computed to construct relative bins. For example, in the sex ratio study (Chapter IV), I tried constructing bins using deciles. I used the 0^{th}–10^{th} percentile, the 10^{th}–20^{th} percentile, etc. until the 90^{th}–100^{th} percentiles as cut-offs. In Chapter V on infant mortality, I tested the use of variables for the 90^{th}–95^{th}, 95^{th}–99^{th}, and 99^{th}–100^{th} percentiles. Finally, count variables indicate the number of days in the exposure period where the daily maximum temperature fell into the 90^{th}–100^{th} percentile of the cluster-specific distribution.

The use of absolute temperature for exposure measurements is often criticized for ignoring place-specific adaptation. This adaptation may be physiological, cultural, and political (Navas-Martín et al., 2024). Regarding physiological adaptation, the argument here is that, for example, a 30°C day will not feel the same to the average individual in Cairo – a location where 30°C days frequently occur throughout several months of the year – compared to the average individual in Sweden – where 30°C days are rare. Hence, the extremeness of temperature, *relative* to the location-specific distribution, may be important. Indeed, some studies indicate that the minimum mortality temperature can shift over time. In the Netherlands, the minimum mortality temperature has decreased over a period of just 23 years (Folkerts et al., 2020). Historical analyses (Yang et al., 2024) and global projections (Yin et al., 2019) of the minimum mortality temperature suggest, too, that this threshold can shift. This evidence indicates that physiological responses to temperature may not be constant and that human physiology can adapt to heat stress.

However, a first counterargument against the use of relative thresholds for reproductive health studies is that evidence for adaptation to heat is still lacking for pregnant individuals. It is known that in the general population demographic and physiological factors shape susceptibility to heat stress (ibid.), but responses of pregnant individuals specifically have not been investigated, to my knowledge. Equivalents of the minimum mortality temperature could be the “maximum fertility temperature”, or “the minimum prenatal mortality temperature”. Further evidence is needed on minimum prenatal mortality temperature levels, their global variation, and their variation over time. This evidence would help us understand to what extent adaptation to heat stress occurs in pregnant individuals.

In addition, while some location-specific adaptation may occur, physiological *limits* to adaptation may be universal across human populations. Indeed, a study (Sherwood & Huber, 2010) indicates that the adaptability limit to heat stress is surprisingly stable across populations. Considering this finding, relative measurements also have an important caveat: They assume there is no limit to human adaptation to heat. If temperature distributions shift even further in the next years (Calvin et al., 2023), the baseline distribution will be raised, from which the relative thresholds are computed. Some adaptation to heat may indeed occur, as suggested in existing literature. But relative exposure measurements ignore the fact that certain levels of temperature will be above the human threshold for thermal comfort nevertheless, or even above the limit of possible adaptation in some locations of the globe – *regardless* of how frequently they occur.

For this reason, relative exposures can make identification difficult. The classification of each day into a relative bin depends on how frequently differing temperature levels occur in the long-term baseline distribution. This means that a 35°C day could be classified into a 90th-100th percentile bin in cold climates. But a 35°C day could be classified into a much lower percentile bin in hot climates. Hence, the classification of the same absolute temperature across different relative bins because of underlying climate differences leads to a conflation of which temperature thresholds are biologically meaningful.

In my studies, I faced this challenge. Temperature effects were always more clearly identified across different intensities when using absolute instead of relative measurements. In my study on infant mortality (Chapter V), I used data on only one population, Mali. This reduced heterogeneity in the baseline temperature distributions of clusters. Here, I was able to identify relative temperature effects. However, they were inconsistent. The estimates indicated that lower relative temperatures had a stronger effect on the outcome than higher ones. This would contradict existing evidence and hypotheses. In Chapter IV on SRBs between Sub-Saharan Africa and India, temperature effects were not identified with relative temperature bins. This may be because of the large within-sample heterogeneity of temperature distributions and climates.

There is a further argument against relative bins that concerns the temporality of exposure attribution. Births in each cluster can occur across several decades. The long-term reference period can span several decades, too. For each cluster, the reference period is the same. This means that a birth early in the reference period will be assigned the same reference distribution as a birth that occurs late in the reference period. For births that occur early in the reference period, the reference period can partially be based on future temperature values that have not even been observed yet in the lifetime of the mother. This seems logically inconsistent. To address this issue, researchers could compute a different reference distribution for each cluster and year of birth. However, this would be computationally intensive, and I am not aware of any studies that have attempted this.

Finally, relative bins limit comparability of estimates across geographic regions and samples. Since the reference distribution differs between locations, so do the absolute values that correspond to the relative thresholds. Absolute thresholds ease interpretation, comparability of estimates between samples, and potential future use of estimates in projections.

To summarize, I use absolute temperature to define cut-offs for the bin method. Relative measurements can conflate days of high heat intensity with less hot days and make identification challenging for this reason. To what extent adaptation of pregnant individuals is possible, has not been investigated in the literature. The use of absolute temperature can provide insight into human thermal comfort levels in a way that is comparable across samples. Importantly, as I will argue below, the modelling strategy employed in my empirical work still accounts for place-specific adaptation with the use of location fixed effects.

2.4 Summary

The empirical chapters of this thesis use exposure variables that are based on measurements of the daily maximum temperature at the DHS cluster location. The variables are constructed as 5°C temperature bins for the exposure period, using absolute temperature thresholds. This method allows for non-linear temperature effects, uncovers the effect of temperature at different intensities, and provides estimates that are comparable across samples. The following section describes how my empirical work models temperature effects on the outcomes under study, using these exposure variables.

3 Modelling the effect of temperature on reproductive health outcomes

To produce estimates of the effect of temperature on the outcome that can be interpreted as causal, the models need to exploit variation in temperature that is random. In the following, I first discuss factors that could potentially confound the relationship between temperature and the outcomes in my empirical work. Then, I describe how time-place fixed effects can control for these confounders and isolate plausibly random temperature variations. This approach is based on Dell et al. (2014) and a growing body of literature on climate impacts on a diverse range of outcomes. I apply this strategy in all my empirical chapters.

3.1 Patterns in temperature variation are non-random

For temperature to be exogenous to the reproductive health outcome, there must be no factor that affects both temperature and the outcome of interest. Hence, confounders need to be ruled out. Which factors could make temperature variation non-random? Temperature variation over a given period of several years is usually systematically associated with several factors. In the following, I describe how seasonality, annual shocks and trends, and geographic differences can lead to confounding. In this effort, I refer to time series terminology.

First, reverse causality can be ruled out as threat to identification. In the context of temperature-health studies, there is usually no concern of reverse causality. For reverse causality to be a concern, the reproductive health outcome would need to cause variation in temperature. One of the very rare settings where any type of human activity has a direct and immediate impact on ambient temperature may be large explosions. Working under the assumption that humans cannot influence ambient temperature, there can be no reverse causality from humans to temperature.

A factor that influences both observed temperature and reproductive health outcomes, are *seasonal cycles*. Typically, temperature variation occurs within seasonal cycles throughout a year. Seasons are predictable patterns that repeat over a fixed time period. As confounders, seasons are associated with systematically patterned variation in both the exposure (temperature) and outcomes under study in this thesis (births, infant mortality, antenatal visits). The literature evidences seasonal patterns in all outcomes under study in this thesis (Cagnacci, 2003; Dorélien, 2016; Doyle, 2023, 2023; Fahey et al., 2019). While some of the seasonal variation in these outcomes may be driven by temperature[14], there are many other factors that can also cause seasonal variation in these outcomes. For example, income, nutrition and food insecurity (Kitsuki & Sakurai, 2023; Sibhatu & Qaim, 2017; Stevens et al., 2017), infectious and non-communicable disease (Basnet et al., 2016; Grassly & Fraser, 2006), ANC utilization (Fahey et al., 2019), contraceptive use (Grace et al., 2023), fertility (Boland et al., 2020; Seiver, 1985), birth health (Currie & Schwandt, 2013), sexual intercourse (Markey & Markey, 2013; Ueda et al., 2020), physical labor such as in agricultural activities, business cycles and many other reproductive health related factors vary throughout the year in cycles that are predictable. Seasons can hence cause temperature and the outcome under study to co-vary. To summarize, temperature-birth linkages are confounded by seasonal factors that are predictable to an extent. Seasonality can differ between populations, which I elaborate on below.

A second factor that can confound the relationship between temperature and the outcomes under study are *annual shocks,* which can constitute outliers or breaks. I aim to illustrate this with the following example. Imagine a given year that is particularly hot. At the same time, it is also a year that suffered from a sharp economic recession that affects reproductive health. Hence, a strong correlation emerges between temperature and the reproductive outcome. Let us assume that temperature has no effect on the reproductive

[14] In fact, the origins of the literature on temperature impacts on fertility and SRBs were studies that aimed to identify seasonal variation in these outcomes (Lam & Miron, 1996; Seiver, 1985; Warren et al., 1980).

health outcome, in fact. In this case, if annual shocks are not controlled for, it may appear that there is a strong relationship between temperature and the reproductive outcome. In fact, this relationship is entirely driven by the economic recession instead of the extreme heat that coincidentally occurred in the same year. This example illustrates how annual shocks to temperature, and the outcome can confound the relationship.

Similarly, *annual trends* can confound the relationship. Unrelated time trends can cause temperature and the outcomes under study to co-vary. For example, the outcomes of SRBs, infant mortality, and ANC visits may exhibit changes over time, brought about by improvements or deteriorations of healthcare services, nutrition, general health conditions, or a range of other factors. At the same time, climate change has led to warming trends in virtually all populations in my samples. Therefore, trends in temperature and the reproductive outcome can correlate over time because of unrelated factors – leading to confounding of the relationship.

Lastly, part of the variation in temperature can be non-random not only across time, but also across space. All confounders described vary significantly across societies and geographies. Seasonal patterns, annual trends and shocks in both temperature and the outcomes show distinct variation across different units. They could be specific to a community or neighborhood, subnational region, country, climate zone, or broader geographic area. For example, rates of temperature increases differ across the globe (Lewis et al., 2019). For example, there can be substantial differences in seasonality, climatic conditions, economic conditions, social institutions, population vulnerability, and reproductive health outcomes even within countries.

The approach laid out by Dell et al. (2014) addresses confounding from seasonality, annual trends, and shocks and can be flexibly adapted to control for such factors across different geographic units. I explain this approach in the following section.

3.2 Fixed effects can isolate the random component of temperature variation

Dell et al. (2014) explain how the use of time-place fixed effects can isolate plausibly random variation in temperature across time. This fixed effects approach first became widely used in climate econometrics. In this field, researchers were keen to exploit the exogeneity of temperature to identify weather impacts on outcomes such as human capital and economic productivity (Barrios et al., 2010; Dell et al., 2012; Hsiang, 2010). Dell et al. (2014) then summarized this approach in a seminal paper to provide methodological guidance. The first application of the method on reproductive health research, to my knowledge, is (Barreca et al., 2018) on temperature impacts on fertility in the US. Particularly in the climate economics literature but also in climate demography, the use of time-place fixed effects has become the best-practice methodology for identifying climate impacts on a range of outcomes (Fishman et al., 2019; Isen et al., 2017; Wilde et al., 2017).

First, to address seasonality induced confounding, Dell et al. (2014) suggest employing *month fixed effects*. With these fixed effects, everything that is time-invariant within a calendar month is controlled for. This approach is equivalent to including dummies for each calendar month in the regression. The idea here is that temperature variation within a calendar month has a *random component*, which fluctuates from year to year. For example, whether there are four or five hot days above >30°C in the January of a given year in Delhi as opposed to only two or three, is plausibly random. This is under the assumption – as I explain further below – that location specific, seasonal factors, and annual trends and shocks are controlled for. The use of month fixed effects isolates the random component of temperature variation. Therefore, the month fixed effects are key to the causal interpretation of results in my empirical chapters. [15]

[15] Alternatively, season fixed effects could be particularly useful for settings where indirect temperature effects could drive variation in the outcome through agricultural productivity, income generation, infectious disease transmission, and other factors. However, in climate studies of reproductive health, season fixed effects have not found application yet, to the best of my knowledge.

Second, annual shocks and trends can be controlled for with calendar *year fixed effect*s. Similarly to month fixed effects, this means including year-dummies in the regression for each year of the observational period. Effectively, these fixed effects control for all factors that are fixed within a year. This means that if a year was generally hotter or the population experienced worse health conditions throughout that year, the fixed effects absorb this variation. They also control for a warming trend.

Third, fixed effects can also be used to make the month and year fixed effects place-specific and to control for place-specific characteristics. The month and year fixed effects should be placed at least at the country level (i.e. country-by-calendar-month fixed effects or country-by-calendar-year fixed effects), or alternatively on the cluster, or district or subnational regional level, or the climate zone level within a country. They then control for all factors that are time-invariant within each time-place unit. The smaller the geographic units, on which the fixed effects are placed, the more temperature variation is absorbed. This leaves less variation from which the temperature effect can be identified off. By extension, the interaction of the place-time fixed effects also control for all fixed characteristics of each place.

The specific choice of fixed effects should reflect the data generating process, empirical evidence, theoretical arguments, and results from triangulation. For example, seasonal patterns vary within larger countries subnationally. For this reason, I employ subnational region (first administrative unit, e.g., states) rather than country fixed effects. Sample size considerations can further influence the choice of fixed effects. The fixed effects approach requires sufficient variation 1) between place-time units and 2) within place-time units. This is particularly important to consider in the investigation of outcomes that vary little over time. For example, SRBs exhibit little variation within populations over time, and also across populations globally (besides populations where sex ratios are skewed because of sex-selective abortion). To increase variation in the analysis, in Chapters III and IV I pool births in Sub-Saharan African countries into one sample. It should be kept in mind that even though the sample is highly heterogeneous, the subnational region-by-month fixed effects still control for region-specific factors on the subnational level.

In my empirical chapters, I arrived at region-month and region-year fixed effects. These are interaction fixed effects where region refers to the subnational region on the first administrative level (e.g. a state). Using these fixed effects also made estimates more precise. This indicates that relevant variation was absorbed by the region fixed effects. I also explored a region-year time trend instead of using single years. Both approaches yielded equivalent results. In Chapter III on ANC, I additionally use cluster fixed effects. These can control for fixed cluster characteristics, including healthcare infrastructure, livelihoods, and social norms. In all my empirical chapters, I explored how different sets of fixed effects change the estimates to understand better which variation is absorbed.

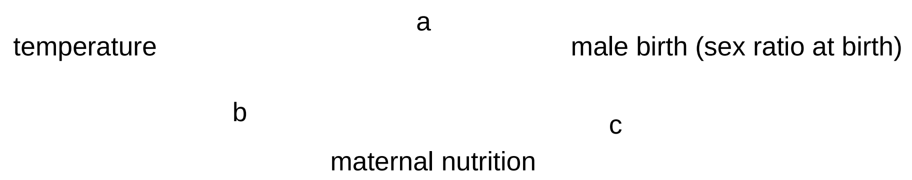
With this set of fixed effects, what variation is left to identify the temperature effects off? The variation that occurs within the same calendar month, but across years in the same geographic unit – beyond variation that is caused by annual shocks in extraordinary years and annual trends over the years. The estimation thus captures the effect of temperature variation on the outcome, given the location and month of the year, while also controlling for annual shocks and trends. The region-month fixed effect is key to my causal interpretation: It limits the temperature variation to the plausibly random fluctuations that occur across years (but within the same subnational region and calendar month). In addition, the region-year fixed effects control for annual shocks and trends on the subnational level.

What alternatives to the fixed effects approach advocated for by Dell et al. (2014) exist for causal identification of temperature impacts? One alternative is the use of natural experiments. Heatwaves (Green et al., 2016) or electricity blackouts that prevent households from using electricity-powered cooling technologies such as fans or air-conditioning can cause exogenous temperature variation. However, these alternative designs have important drawbacks. If the interest is to study cyclical and intermittent temperature effects, the focus on heatwaves is too limited on a major shock event. Physiological and behavioural responses to shock events can differ from responses to expected and intermittent temperature exposure. In addition, shock events are always grounded in a specific place and time, with potentially limited temperature variation in intensity and duration, as well as across spaces and populations with different characteristics, ultimately prompting important questions around external validity.

3.3 Overcontrolling from parental characteristics

While confounders should be controlled for when estimating the causal temperature effect on the outcomes under study in my thesis, controlling for parental characteristics can lead to over-controlling. Confounders affect both the independent variable and the outcome. Parental characteristics, however, might be correlated with temperature but are unlikely to affect temperature. Here, the direction of the relationship between temperature and the omitted variable is crucial. Importantly, if the omitted variable is itself an outcome of the temperature exposure, then including this variable in the estimation could lead to over-controlling.

Figure 4: Directed acyclic graph for the effect of temperature on the sex ratio at birth through maternal nutrition



The over-controlling problem arising from parental characteristics can be illustrated with an example (**Figure 4**). In Chapter IV, the outcome of interest is the SRB, and the independent variables capture gestational temperature exposure. Should maternal nutrition be controlled for to avoid omitted variable bias? Maternal nutrition can correlate with both temperature exposure (independent variable) and SRBs (outcome). The correlation is unlikely to stem from maternal nutrition influencing weather variation.

Instead, the correlation between maternal nutrition and temperature most likely arises because temperature causes variation in maternal nutrition directly or indirectly (pathway b). Maternal nutrition may then in turn induce sex ratio changes (pathway c). This means that part of the temperature effect on the sex ratio may function through maternal nutrition. In this setting, controlling for maternal nutrition would partially eliminate the explanatory power of temperature on the sex ratio at birth. Closing the causal pathway between temperature and maternal nutrition (b) would reduce the total effect of temperature (a, b, c) on sex ratios to the effect of temperature beside the maternal nutrition pathway (pathway a only). Inclusion of the parental control would therefore not necessarily produce more precise estimates of the total effect of temperature.

How estimates change upon inclusion of observed omitted variables in the model can in theory be tested, but this is difficult with DHS data. The surveys report very limited information on time-varying parental characteristics. DHS only captures maternal health variables, such as BMI and anemia status, at the time of the interview. Hence, maternal health factors cannot be controlled for at the time of the temperature shock effectively. They are only observed once over the mother's life-course, at a time point that could even be after the birth.

To work around the limited information on time-varying parental characteristics, one strategy is to at least control for time-invariant parental characteristics. One way of doing so is by using mother fixed effects. Mother fixed effects capture some of the variation in health and nutrition between mothers. In fact, this approach can capture more factors than would be possible to control for if one was to rely on observed variables. This advantage arises because mother fixed effects capture both observed *and* unobserved variables – in so far as they are time-constant within a mother. Thereby, mother fixed effects not only account for maternal nutrition and health, but control for *all* factors which do not vary over the course of a woman's childbearing years, such as education, SES, race/ethnicity, underlying health caused by genetics, upbringing, etc. The fixed effects also control for time-invariant factors in the mother's environment, such as social, cultural, geographic, financial and other factors that vary by mother. In Chapter IV on sex ratios, I add such mother fixed effects to the original regression specification to conduct a robustness check. I find that the heat effects on male birth probability are even more pronounced. However, I do not use mother fixed effects in my main specifications because they limit the sample to mothers who have at least two birth records in the sample (for further explanation, **see Appendix 4**).

To conclude, Dell et al. (2014) present a convincing argument based on a range of climate econometric studies. They suggest that time and place fixed effects can control for the variation that makes temperature variation temporally and spatially non-random. Controlling for parental characteristics likely induces an over-controlling problem that reduces the explanatory power of temperature on the reproductive outcome. For this reason, I estimate the effect of temperature on ANC visits (Chapter III) and on SRBs (Chapter IV) without parental controls. Below I address in more detail how I conceptualize the role of parental characteristics instead.

3.4 The role of SES and other stratifying variables as effect modifiers

An important question is how the role of SES and other stratifying variables in temperature-health relationships should be conceptualized with view to causal identification. Mothers with higher SES may benefit from a range of advantages that reduce their susceptibility to heat-induced adverse reproductive outcomes. For example, one of the advantages that higher SES may afford is access to cooling technologies (Davis et al., 2021) and insulated housing (Braubach & Fairburn, 2010; Zhang et al., 2025). Based on this reasoning, some might argue that mothers are in fact *exposed* to lower temperatures. Hence, controlling for SES should be necessary. This reasoning is in line with studies on natural disasters that show SES is an important factor that determines exposure to the disaster in the first place, for example because of residential segregation

(Muttarak, 2022). Crucially, this reasoning assumes that SES causes variation in temperature.

However, this logic would misunderstand the data generating process and the independent variable of interest in my studies. The true temperature at a geographic location is not influenced by the SES of a particular mother. More broadly, my interest lies in identifying the effect of *weather* variation on health outcomes. This interest responds to a larger research question of how reproduction and health are embedded into the natural environment. It also embeds my empirical work into the literature on the concurrent and future impacts of climate change on human populations. Conceptually, this is different from aiming to identify the effect of temperature variation in the mother's immediate surrounding on her health outcomes.

Instead, given that I am interested in the effect of weather variation on health outcomes, this allows me to regard the role of SES as an *effect modifier*. Two mothers of different SES at the same location will be attributed the same observed value in weather (temperature). What differs between them is their underlying vulnerability to heat exposure. This vulnerability encompasses their capacity to anticipate, cope with, and recover from the temperature exposure physiologically and in other ways. Hence, temperature affects the outcome, while SES, health conditions, and other maternal characteristics can moderate the relationship. SES and other stratifying variables are indeed extremely salient factors. Their study furthers our understanding of how interventions can help protect mothers from adverse heat impacts. Integrating these variables into my framework as moderating variables allows me to conceptualize them as factors that influence the more fundamental relationship that exists between the environment and human reproduction and health.

One could also argue that there is a risk that mothers of lower SES live in hotter locations. This effect, however, is controlled for with the region level fixed effects. These fixed effects produce a within-region estimate.

The role of SES and other stratifying variables can be modelled with heterogeneity tests. In my empirical chapters, I conduct heterogeneity analyses by running separate regressions for each subgroup. Alternatively, one could analyze heterogeneity using interactions of the temperature exposure variable with the effect moderator. However, in my work on sex ratios and ANC (Chapters III and IV), I have at least five temperature exposure variables (the bins) for each exposure period. It would be difficult to interpret the interactions of all exposure variables with each level of the stratifying variable. For example, for four maternal age groups, interactions would yield 60 coefficients (5 temperature bins times 3 trimesters times 4 maternal age groups). Therefore, I instead run separate regression analyses for each population subgroup. The results from these separate regressions have the disadvantage that tests of the difference in coefficients are more difficult. Nevertheless, the heterogeneity tests in my chapters point to not only vulnerability but also mechanisms that link exposure and outcome. This is an important contribution of my empirical work, as I argue in Chapter I (Introduction).

3.5 Precipitation as an omitted variable

Rainfall is a key climatic variable that can covary with temperature but is not itself caused by temperature in the short-term. Several meteorological studies show that temperature and rainfall tend to be correlated over time and that the direction of the correlation can vary by region (Adler et al., 2008; Auffhammer et al., 2013; Trenberth & Shea, 2005). These studies suggest that temperature records should not be interpreted without considering their covariation with precipitation. While rainfall may be correlated with temperature, rainfall can independently affect reproductive health outcomes through mechanisms such as infectious disease transmission and nutrition (Chowdhury et al., 2018; Dimitrova et al., 2022; Mank et al., 2021; Randell et al., 2022). Therefore, controlling for rainfall helps isolate the effect of temperature by accounting for their co-variation to avoid omitted variable bias. Hence, all my empirical studies control for rainfall in the gestational period.

While a similar argument could be made to include relative humidity in the model, my empirical work does not include humidity controls. Arguably, this is a limitation of my thesis. From a practical perspective, I was unable to identify datasets on humidity with the same temporal coverage and spatial resolution as my main treatment variables on heat exposure and the rainfall controls. Some of the variation in humidity will be captured by the rainfall controls. But rainfall and humidity capture different environmental conditions. However, for the study on SRBs (Chapter IV), I include a supplementary analysis with wet-bulb-globe-temperature (WBGT). Wet-bulb-globe-temperature is a non-linear combination of heat, humidity, and radiation conditions. The results showed that temperature impacts are not clearly identified when using wet-bulb-globe-temperature data to measure heat exposure. This finding suggests that humidity may be less salient in shaping the sex ratio at birth.

3.6 Summary

To summarize, patterns in temperature variation over time are non-random. The relationship between temperature exposure and the outcomes under study in my empirical chapters (SRBs, ANC, and infant mortality) can be confounded by seasonal cycles, annual trends, and annual shocks. Month and year fixed effects on the subnational regional level can control for these confounders on the subnational level. While controlling for parental characteristics can lead to overcontrolling, variables on parental characteristics can serve as stratifying variables that moderate the relationship between temperature and the outcome and point to vulnerability and mechanisms. Precipitation can covary with temperature and should be controlled for to avoid omitted variable bias.

4 Conclusion

This chapter responded to the variety of methodological approaches chosen in the existing literature on temperature impacts on reproductive and infant health and presented a consistent methodological framework that provides practical guidance on temperature-birth linkages, with specific application to micro-level birth records from the DHS and high-resolution, gridded temperature data. The framework encompasses the choice of data sources, construction of measurements, and statistical analyses with a causal identification strategy. The following empirical chapters demonstrate how the consistent application of this best-practice methodology can advance our understanding of temperature impacts on a range of different maternal and infant health outcomes in diverse settings.

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Appendix

Appendix 1: Coverage challenges

For example, CHIRTS is a commonly used data source because it offers daily temperature information on a global grid at fine spatial resolution (0.1 degrees). However, CHIRTS only covers years 1983 to 2016. A linkage with DHS births is then only possible for births that fall into this period, but not for births after 2016, where 54 further DHS surveys were conducted (The DHS Program, n.d.-c). The 2020 DHS surveys in India were also conducted later and this survey provides a large sample size of almost 2 million live births. If researchers are aiming to use birth histories from all available DHS surveys, they face the choice of either limiting the birth records to 1983 to 2016 or utilizing a different data source with more extensive temporal coverage (I chose the latter option and utilized ERA5 data, see below).

A second challenge concerning coverage is specific to the use of weather station data (as opposed to gridded reanalysis datasets that draw on many data sources, see more on this below). Station coverage and density vary highly across geographic regions in ways that are usually not random (Ortiz-Bobea, 2021). This is because station distribution often depends on factors such as population density, funding, and research needs. Given that missingness in climate observations is often non-random, researchers are forced to make a decision: They can either 1) use the non-random sample where weather station information is available or 2) extrapolate the available weather station information to larger geographical areas around the weather station, likely increasing exposure misclassification. The latter approach forces the environmental exposure variables to have the same value (or “intensity”) at adjacent geographic locations. How problematic this homogeneity assumption is depends on how much the environmental exposure varies over spatial units, and how large the distance is across which the measurement is extrapolated. Usually, this approach is expected to result in exposure misclassification that would bias analysis estimates toward the null because inaccurate temperature climatic conditions are attributed to some records. As opposed to air pollution conditions, temperature conditions vary little over several kilometers.

Appendix 2: Spatial resolution in time series or weather station data

In contrast to gridded datasets, for time series datasets spatial resolution refers to whether the data is provided on the country, subnational regional, or municipality level. E.g., for each time point (see temporal resolution), country level data provides one measurement at time t for each country. For clarity, this is not to be confused with the spatial coverage. A dataset can cover several countries (spatial coverage) but provide data on the country level, with one measurement for each country per time point (spatial resolution).

Appendix 3: Disentangling maternal and paternal environmental exposures in the pre-conception period

While to date there is no research on the role of paternal heat exposure for shaping outcomes at birth and after birth, paternal health and exposure may have an underappreciated function in the relationship between temperature and maternal and infant health outcomes. Unfortunately, however, it is extremely difficult to disentangle maternal and paternal environmental exposures before conception, as the parents need to be at the same location for conception to occur. Hence, the parents' environmental exposures during conception always overlap. This challenge likely partially explains the research gap on the role of paternal environmental exposures more generally. The challenge may only be overcome with detailed, georeferenced residence and mobility histories for both parents that would capture differences in their locations before sexual intercourse and allow for leveraging this variation between maternal and paternal exposures.

Appendix 4: Mother fixed effects

Mother fixed effects shift the analysis sample towards a specific subgroup of births. On the one hand, the fixed effects are effective in controlling for a range of observed and unobserved maternal factors, as described. On the other hand, they limit the sample to mothers who have at least two birth records in the analysis sample[16]. Because of the limited variation within some mothers, the analysis sample shifts. Fixed effects can only identify the temperature effect off within-group (i.e. within mother) variation. Hence, if there is no variation within a mother because there is only one birth record for the mother, the record of this mother will be dropped in the estimation. There is reason to assume that mothers with only one live birth (a first birth) might be a selected group. So, their exclusion could lead to a different composition of the analysis sample in terms of health and social characteristics than the general population of mothers.

[16] There are two main reasons why mothers might have fewer than two birth records in the analysis sample. Firstly, some mothers only have one live birth in their reproductive period. Secondly, the sample's time period can limit birth records. For example, the DHS Children's Recode only captures births in the five years prior to the interview year, unlike the DHS Births Recode that captures full birth histories. In Chapter V on infant mortality, I only use the Children's Recode to limit recall error on infant death dates. Chapter III on ANC also only has information on antenatal visits for births in the previous five years.
It should be kept in mind that, in the first place, both the DHS Births Recode, and the Children's Recode only include mothers who have at least one live birth, as the unit of analysis is a live birth or child

Chapter III: Extreme heat reduces antenatal care visits in vulnerable low- and middle-income countries

Empirical chapter 1

Co-authorship note: This chapter is based on solo-authored work. No co-authorship contributions to declare.

Publication note: This work is currently unpublished.

Chapter III: Extreme heat reduces antenatal care visits in vulnerable low- and middle-income countries

Abstract: The World Health Organization (WHO) recommends a minimum of eight antenatal care visits during pregnancy, a target since 2016 that has shaped global maternal health benchmarks and investment priorities. Rises in temperatures globally, however, threaten to stall or reverse progress in expanding antenatal care coverage by disrupting access to healthcare services. In this study, I investigate the impact of exposure to extreme heat during pregnancy on antenatal care utilization across 52 low- and middle-income countries around the world. For this, I merge Demographic and Health Survey data on more than 860,000 live births with hourly high-resolution, gridded temperature data for each pregnancy. The findings indicate that heat exposure above 35°C during gestation is overall associated with a reduction in antenatal care visits in LMICs, but particularly in Sub-Saharan Africa. Large inequities exist between world regions and within Sub-Saharan Africa, where ANC coverage is still comparatively low. Adverse heat impacts are particularly pronounced for mothers who face significant barriers in accessing healthcare more generally, have lower socioeconomic attainment, live in rural areas, and have limited agency in household decisions. This study underscores the need for targeted interventions to ensure maternal healthcare access in the most vulnerable populations across the world under intensifying climate stress.

1 Background

Antenatal care (ANC) can save lives and is crucial to a positive pregnancy experience because it can ensure that pregnancy complications are detected and treated, provide health promotion, and prevent diseases at a critical time period of women's lives. The WHO recommends a minimum of eight antenatal care contacts during pregnancy since 2016 (WHO 2016). This target shapes global maternal health benchmarks and investment priorities, including SDG 3.7 on universal access to sexual and reproductive healthcare services (UNDESA, n.d.). Climate change has been recognized as a threat to reproductive and infant health, especially in low- and middle-income countries (LMICs). Extreme heat in particular increases the risk of delivery complications, neonatal mortality, stillbirth, preterm birth, and low birthweight (Dimitrova et al. 2024; McElroy et al. 2022; Hanson et al. 2024; Barreca and Schaller 2020). An assessment of heat impacts on ANC can provide important insight to policymakers for developing adaptation interventions that ensure every woman receives access to ANC.

Disruptions in healthcare and ANC induced by environmental irregularities have received some attention in epidemiological studies. Concentrated shock events, such as flooding, earthquakes, and hurricanes, can impede healthcare infrastructure and access to sexual and reproductive healthcare services (Murray-Watson et al. 2025; Behrman and Weitzman 2016; Kissinger et al. 2007). Extreme heat has been linked to adaptations in mobility and transport behaviour (Yucel et al. 2025; Fan et al. 2023), and in high-income contexts to reduced health care utilization (Samano et al. 2021; Si et al. 2019). These findings indicate individuals strategically reduce dangerous outdoor heat. Particularly pregnant women may aim to avoid harm to their pregnancy from direct heat exposure that can induce fetal strain (Bonell et al. 2022). Further plausible mechanisms preventing ANC access under heat include immobility from heat-related illness (Faurie et al. 2022) and indirect temperature impacts on livelihoods (Kroeger 2023; Romanello et al. 2022), female decision-making capacity (van Daalen et al. 2022), and productivity of health service provision (Kjellstrom et al. 2016).

Sufficient ANC is lacking for substantial parts of the population in many LMICs. In 2023, 50 % of pregnant reproductive-age women in low-income countries, and 34.8 % in lower middle-income countries still attended less than four ANC visits during pregnancy by any provider[17] (UNICEF 2025). At the same time, LMIC populations bear a disproportionate

[17] Country classification is based on the World Bank’s classification, see UNICEF Data Warehouse.

burden of extreme heat exposure (Bianco et al. 2024; Green et al. 2019), driven by both rapid increases in frequency, intensity and duration of extreme heat (Meehl and Tebaldi 2004; Coffel et al. 2018; Perkins-Kirkpatrick and Lewis 2020) and population growth (Tuholske et al. 2021). It is estimated that in urban areas, exposure to wet-bulb-globe temperature above 30°C globally increased nearly 200% from 1983 to 2016 (Tuholske et al. 2021). While extreme heat poses a major threat to human health and well-being in LMICs, no study has assessed the impact of extreme heat on ANC.

This study is the first investigation of temperature impacts on antenatal and birth care in LMICs. I conduct a micro-level linkage of 862,521 birth records by 827,062 mothers across 52 countries in the period 1985–2024 from the georeferenced Demographic and Health Surveys (DHS) with gridded, high-resolution temperature data at the mother's residence location during pregnancy. The results provide seasonality-adjusted estimates for the impact of temperature at varying intensity thresholds on ANC visits across LMICs. Drivers related to socioeconomic disadvantage, female empowerment, and healthcare accessibility that may make mothers particularly vulnerable to heat impacts on antenatal care are assessed. The insights from this study can be used for targeted interventions that aim to improve ANC access in LMICs under a warming climate.

2 Data and methods

2.1 Data

I draw on two data sources to investigate the impact of ambient temperature during pregnancy on antenatal care visits. Firstly, I use birth records from the Births Recode files from the Demographic and Health Surveys (DHS). These are cross-sectional, harmonized, nationally representative surveys of reproductive aged women conducted across low- and middle-income countries. They provide birth histories, alongside information on the infant, childbirth, and the mother's sociodemographic characteristics. I restrict the analysis to surveys that provide the geolocation of the Primary Sampling Unit

(PSU), i.e. latitude and longitude information of a group of households that usually corresponds to a city block or village.

The analysis sample includes 862,521 births between 1985 and 2024 from 126 georeferenced surveys conducted in 52 countries between 1990 and 2023 (for the full list of countries, surveys, and observations per survey, please refer to **Appendix Table 1**). I restrict the sample to births to women aged 15–45 at birth. DHS records ANC information only for any last birth of the respondent that took place in the five years before the interview to limit recall error. Mothers who were not resident at the PSU location of the interview in the year leading up to birth are excluded from the analysis to limit exposure attribution error (excluded N = 528,011).[18] Observations from PSUs with incorrect latitude and longitude information were also dropped (N= 1,085).

Second, I conduct a micro-level linkage by connecting each birth with temperature and rainfall conditions for the approximate pregnancy duration. I extract temperature and precipitation data at the mother's PSU location for each day in the approximate pregnancy period, drawing on the ERA5-Land hourly dataset from 1950 to present, available at the Copernicus Climate Data Store (https://cds.climate.copernicus.eu). The ERA5 reanalysis products draw on in-situ observations from a range of data sources, including satellites, land stations, drifting buoys, radars, radiosondes, and aircraft data (ECMWF 2025). Unlike other data sources, ERA5-Land goes back far enough in time to cover births from earlier surveys in the sample. In addition, it provides hourly temperature information on a fine resolution grid of 0.1×0.1 degrees (ca. 9 km^2 grid cells at the equator). ERA5-Land was specifically adjusted to provide reliable estimates for land surfaces (Copernicus Climate Change Service 2019). I aggregate the ERA5's hourly values to daily values for maximum temperature and total rainfall. To address random spatial displacement of the PSU locations by up to 10 km, which the DHS undertakes to prevent respondents' identification, I draw a 10 km buffer around each PSU and extract the temperature and

[18] While this approach limits exposure attribution error, it limits our sample to mothers who did not migrate recently.

rainfall data for all intersecting grid cells. Daily maximum temperature and daily total rainfall are then computed as the average of the values from all intersecting grid cells, using weights that correspond to the proportional area of each grid cell that intersects with the buffer.

2.2 Variables

Antenatal care visits (outcome): The outcome variable is a count variable that indicates the number of ANC visits the mother had for the pregnancy.

Temperature exposure during pregnancy (treatment): The treatment variables are six count variables (based on six bins: 0-15°C, 15-20°C, 20-25°C, 25-30°C, 30-35°C, and >35°C) for the approximated gestational period. Each of these variables indicates the number of days in gestation where the daily maximum temperature fell into a respective 5°C bin. I use absolute temperature instead of relative temperature thresholds (e.g. deciles of the PSU-specific distribution) because they uniformly capture heat stress across locations. While some adaptation to extreme heat takes place, there is a limit to human adaptability to climate change, which is similar across diverse climates (Sherwood and Huber 2010). In addition, differences in local climates are controlled for with fixed effects on the PSU and subnational region level. Across diverse populations, these fixed effects plausibly control for adaptation to heat frequency, intensity, and duration that takes place over longer time periods but also seasonal acclimation throughout the years and within each year (e.g. a particularly hot year).

The binning method has several advantages over coarser exposure variables. First, the method exploits daily variation in temperature as opposed to coarser annual summary measures or z-scores that cannot capture temperature variation during the gestational period. Second, this method provides estimates at varying thresholds of temperature intensity, moving beyond an investigation of only extreme levels of heat intensity that can obscure relevant responses at lower temperatures. Third, the approach makes little assumptions about what the relevant heat threshold should be, as insight on this constitutes a gap in the literature. Fourth, with the 5°C bins the model can capture non-linearity in the impact of temperature on the outcome. Accounting for non-linearity in the model is important as the effect of a hot day above 35°C might differ from the effect of a mild 20-25°C day. The binning method is based on a widely employed econometric technique (Dell et al. 2014) and has been applied to estimate temperature impacts on gestation specifically (Barreca et al. 2018).

The exposure variables are based on an approximation of the gestational duration. Only more recent DHS surveys provide information on the day of birth and gestational length, instead of just the birth month. The subsample with information on gestational length was too small for an analysis. Hence, this study approximates the gestational duration using the birth month and the nine months prior to the birth month.

Control variables: The model aims to isolate the effect of random temperature variations on births while controlling for potential confounders that affect the exposure and the outcome. Precipitation could act as a confounder in the temperature-ANC relationship; hence all models control for total precipitation in the approximate gestational month, covering the month of birth and the nine preceding months. Meteorological studies show that temperature and precipitation correlate significantly over time (Adler et al. 2008; Trenberth and Shea 2005). Rainfall could impact various factors that influence ANC visits indirectly, such as income availability, infectious disease, and nutrition.

Stratifying variables: Heterogeneity analyses can show whether the impact of extreme heat on ANC visits varies by sociodemographic characteristics of the mother and infant, disadvantages in access to healthcare and concerns regarding the healthcare provider, and differences in female empowerment in household decision-making.

The stratifying variables used include education (none/primary, secondary, higher), wealth (five country-specific wealth quintiles), residence (urban, rural location of the PSU), maternal age at birth (15-19, 20-24, 25-29, 30-34, 35+ years), infant birth order based on the mother’s live births (1, 2, 3, 4, 5+), and infant sex (male, female).

Information on barriers to accessing healthcare for the respondent comes from a questionnaire battery that asks the respondent whether the following factors constitute no problem, a small problem, or a big problem: Getting money to go, distance to the health facility, having to take transport, not wanting to go alone. Investigating differences between types of barriers can provide insight into mechanisms at play.

Further barriers capture concerns around the health provider: The concern that there may not be a female health provider, and that there may not be a provider. The subsample on concerns of whether drugs are available at the health facility was too small for the analysis.

Lastly, several stratifying variables are constructed to capture female empowerment through decision-making capacity. These include whether getting permission to go is a problem, and whether the respondent has the final say alone, jointly with the partner or someone else, or someone else has the final say in decisions on the respondent's healthcare, daily purchases, big purchases, husband's earnings, and family visits. I also explored the use of an index that captures involvement in household decisions (categories: involved in all, some, and no decisions) and in financial decisions based on whether the respondent has the final say in daily purchases, big purchases, and husband's earnings (same categories). However, the subsamples that responded to all of the DHS questions regarding decision-making which were needed to construct the indices were too small.

2.3 Empirical strategy

The effect of temperature exposure on antenatal care visits is estimated using a negative binomial model, specified as follows:

$$\log ANC_{icrmy} = \sum_{j}^{J} \beta_{c,p}^{j} TEMP_{c,p}^{j} + rain_{r,m-k} + \alpha_{rm} + \delta_{ry} + \lambda_{c} + \varepsilon_{icrmy} \qquad (1)$$

where the count outcome variable indicates the number of antenatal care visits of child i born in PSU (cluster) c of subnational region r in month m of year y. TEMP is a vector that indicates the number of days in the approximate gestational period p (where the maximum temperature at the PSU falls into bin j (<15°C, 15-20°C, 25-30°C, 30-35°C, >35°C). Hence, the model provides one individual estimate for each temperature threshold for the gestational period. The 20-25°C bin is excluded in the regression as the reference category. An effect estimate hence indicates the effect of one additional day (i.e. a 1-unit change) in the pregnancy, where the temperature falls into the respective bin j (e.g. an additional >35°C day), relative to if it had been a 20-25°C day. $rain_{r,m-k}$ is a control for the total amount of rainfall in each month of the approximated gestational period, which includes the month of birth (k=0) and the nine preceding months (k=1 to k=9).

The fixed effects α_{rm} control for all observed and unobserved factors that are time-invariant within a region-by-month-of-birth combination, where the region is the first administrative unit (e.g. states) on the subnational level. These fixed effects are important as there can be significant seasonal fluctuation in weather, ANC utilization (Fahey et al. 2019; Stone et al. 2020), and fertility (Dorélien 2016). Effectively the fixed effects control for seasonal variation in weather, ANC utilization, fertility composition, agricultural production, livelihoods and income, population health, and sociocultural factors, in so far as they are stable across years within the respective region-month unit. Additionally, δ_{ry} is a region-year fixed effect that controls for annual trends and annual shocks on the subnational regional level, such as economic shocks and warming trends. Lastly, λ_c is a PSU fixed effect that controls for all observed and unobserved factors that are time-invariant on the village (or city block) level. These can include the location's geographic characteristics, social norms, infrastructure, livelihood generation, etc.

Changes in healthcare infrastructure are controlled for in two ways. First, if national policies influence ANC visits, variation from such changes is absorbed by the subnational region-year fixed effects. These fixed effects effectively control for all annual shocks on the regional level (even if several regions experience the same shock), which goes beyond capturing shocks only on the country level. Second, changes in healthcare infrastructure due to health facility additions or other facility changes are captured by the region-year fixed effects, too. While health facility additions could in theory have localized impacts, their coverage usually extends beyond the village (or city block) location. This makes using region-year fixed effects (rather than cluster-year fixed effects) meaningful to control for such health facility changes. I tested the use of cluster-year fixed effects, too. But given that there are more than 96,000 clusters, and each cluster has 40 unique year combinations (1985-2024), the 3.8 million resulting fixed effects exceeded the sample size.

Heterogeneity analyses: For the heterogeneity analyses, a subsample is constructed for each level of each stratifying variable. Regressions are run separately for each subsample. For example, there are three separate regressions for education – one for none/primary educated mothers, one for secondary educated mothers, and one for higher educated mothers.

Interpretation of coefficients: Coefficients from the negative binomial model indicate the effect of one additional day in the pregnancy where the daily maximum temperature falls into the respective temperature bin j on the expected log count of ANC visits. For ease of interpretation and for comparability across subsamples, all figures and descriptions translate these results into percent changes in the expected count of ANC visits. The figures depict the percent changes for each subsample on the same scale. The magnitude of the effect in terms of the resulting absolute change in the expected number of ANC visits depends on the mean number of visits in the subsample and observed heat exposure variation. Hence, the same percent change in ANC visits across subsamples does not necessarily result in the same change in the number of expected visits. For this reason, in Appendix Table 2 the percent changes are translated into the absolute change in the expected count of ANC visits for each subsample.

3 Results

3.1 Descriptive statistics

The analysis is based on a sample of 862,521 births in 52 LMICs (126 DHS surveys) in 1985 to 2024 by 827,062 mothers at 96,245 primary sampling units (PSUs), which correspond to a village in rural and a city block in urban areas (see Table 1). Sub-Saharan Africa (44.7%) and India (30.2%) contribute the majority of births to the pooled sample. The pooled sample's mean number of ANC visits per pregnancy is 4.18 (SD = 3.9). However, there is substantial variation in the mean number of ANC visits across PSU locations (**Fig. 1a**). PSUs with four or more visits cluster particularly in Latin America and the Caribbean as well as in southern India, Central Asia, and West Asia. By contrast, PSUs with very low ANC means cluster in Northeast India, Cambodia, Ethiopia, and Sub-Saharan Africa – especially in the Sahel region, including Mauritania, Mali, Niger, Nigeria.

Table 1: Descriptive statistics

Variable	**Mean (standard deviation) / Frequency (percentage)**
Sample	
N (births)	862,521 (100.00%)
Mothers	827,062
Primary sampling units (PSUs)	96,245
World regions	
Sub-Saharan Africa	385,754 (44.7%)
India	260,217 (30.2%)
North Africa & West Asia	76,410 (8.8%)
South & Southeast Asia	71,730 (8.3%)

Latin America & Caribbean	59,327 (6.9%)
Central Asia	4,992 (0.6%)
Southern & Eastern Europe	4,091 (0.5%)
Outcome	
Number of antenatal care visits (pregnancy)	4.18 (3.91)
Temperature exposure variables	
Number of days in pregnancy	
<10°C days	3.04 (18.65)
10–15°C days	6.32 (27.28)
15–20°C days	16.15 (34.07)
20–25°C days	46.77 (57.05)
25–30°C days	103.29 (69.89)
30–35°C days	84.63 (57.56)
>35°C days	44.18 (53.81)
Controls	
Average rainfall	
t–0 (month of birth)	0.0424 (0.0596)
t–1	0.0426 (0.0600)
t–2	0.0424 (0.0600)
t–3	0.0423 (0.0600)
t–4	0.0426 (0.0601)
t–5	0.043 (0.0606)
t–6	0.0433 (0.061)
t–7	0.0429 (0.0607)
t–8	0.0424 (0.0604)
t–9	0.042 (0.0600)
Stratifying variables	
Maternal education	
None/primary education	525,154 (60.9%)
Secondary education	274,632 (31.8%)
Higher education	62,070 (7.2%)
Wealth	

Poorest	147,425 (17.1%)
Poorer	169,081 (19.6%)
Middle	103,850 (12%)
Richer	259,816 (30.1%)
Richest	34,960 (4.1%)
Residence	
Rural	614,301 (71.2%)
Urban	248,220 (28.8%)
Birth order	
1	157,512 (18.3%)
2	225,397 (26.1%)
3	157,361 (18.2%)
4	105,725 (12.3%)
5+	216,526 (25.1%)
Maternal age at birth	
15–19	90,709 (10.5%)
20–24	250,432 (29%)
25–29	241,859 (28%)
30–34 years	154,667 (17.9%)
35+ years	124,854 (14.5%)

Note: Sample size in the analysis samples can differ because some observations are excluded in the regressions due to lack of ANC variation within fixed effects.

On average there are less than ten days per pregnancy where the daily maximum temperature falls below 15°C, 16 days with 15-20°C temperature, 47 days with 20-25°C temperature, 103 days with 25-30°C temperature, and 85 days with 30-35°C temperature. The category for extreme heat above 35°C counts on average 44 days. However, there is substantial variation in extreme heat days (35°C) across PSUs, too (**Fig. 1b**). In most of the geographic area covered by the georeferenced DHS, there are less than 25 extreme heat days during pregnancy. Fewer extreme heat days are particularly apparent in Latin America and the Caribbean as well as southern Africa. Extreme heat days cluster in the

Sahel region, particularly in Mauritania, Mali, Niger, and Nigeria, as well as in the Northeast of India. Here, occurrence of more than 125 heat days in pregnancy is common.

Fig. 1: Variation in mean number of ANC visits (**a**) and in >35°C days during pregnancy per primary sampling unit (PSU) from georeferenced DHS surveys (**b**) for the births of the pooled analysis sample. PSUs usually refer to a village in a rural and a city block in an urban area. N=96,245.

3.2 Temperature impacts on ANC visits across world regions and countries

In the pooled sample of 52 LMICs (**Fig. 2a**), one additional heat day above 35°C is associated with a .23 % decrease in ANC visits across countries ($p = .000$). This translates into an 11.6 % decrease in ANC visits for a 1-SD increase in >35°C days during pregnancy (SD = 53.8). In absolute terms, a 1-SD increase would reduce the mean of 4.18 ANC visits per pregnancy by .48 to 3.69 expected visits. A small increase in ANC visits for 30-35°C days is apparent by .03 % for one additional day ($p = .045$). No effect on ANC is apparent for temperature below 25°C.

The impact of temperature on ANC visits shows significant variation between world regions (**Fig. 2b-f**). The reduction in ANC for 35°C days is driven by Sub-Saharan Africa (**Fig. d**). Here, one additional 35°C day induces an even larger reduction in ANC visits by .26 % (or 15.9 % for a 1-SD increase, SD = 65.5, $p = .000$). Sub-Saharan Africa's sample mean of 3.63 is already lower than the pooled sample's mean, leading to a reduction to 3.06 expected visits by 0.58 ($p = .001$). In addition, cold days are associated with a similarly large reduction in ANC visits by .28% for one additional <10°C day. But given that such days do not frequently occur in Sub-Saharan Africa (SD = 3.7), the resulting 1.02 % decrease in expected ANC visits for a 1-SD exposure increase is comparatively smaller. The ANC response to both cold and hot days gives the relationship between temperature and ANC in Sub-Saharan Africa a u-shaped curve that is not apparent in other regions.

In contrast to the ANC reductions in Sub-Saharan Africa, India does not exhibit statistically significant changes in ANC visits in response to temperature at any intensity (**Fig. 2b**). Effect estimates for exposure above 25°C are precisely estimated due to the large sample size and effect estimates are negative, but no statistically significant response is apparent.

Latin America and the Caribbean (**Fig. 2c**) as well as South and Southeast Asia (excluding India) (**Fig. 2e)** exhibit gradual increases in ANC visits with rising temperature, but no reductions in ANC at any temperature intensity. In South and Southeast Asia, this increase is apparent from 25°C upwards. In Latin America and the Caribbean, increases are only apparent from 30°C ($p = .056$) and significant for 35°C ($p = .028$). In both regions, the magnitude of the increases in expected ANC visits is smaller than the reductions observed in Sub-Saharan Africa. South and Southeast Asia show a .05 to .19 % increase in ANC (or 3.71 to 4.13 % for a 1-SD increase in heat exposure days). The sample mean is 3.64, and a 1-SD increase in days above 25°C would result in an absolute increase in

ANC visits by .14 to .16 visits. In Latin America and the Caribbean, a 30-35°C increases ANC visits by .06 % (or 4.1 % for a 1-SD increase, SD = 65.2), and a 35°C day leads to an increase by .2 % (or .85 % for a 1-SD increase, SD = 4.2). A 1-SD increase in 35°C days would result in 6.32 expected visit, from the 6.28 ANC mean. In North Africa and West Asia, effect estimates are consistently negative but standard errors are large (**Fig. 2f**). The same issue applied to results for Central Asia and Southern and Eastern Europe.

Focusing on the impact of extreme heat above 35°C on the country level (**Fig. 2g**), most contexts show reductions in ANC visits under heat, particularly in Sub-Saharan Africa. The countries that exhibit statistically significant decreases in ANC visits for temperature above 35°C are Nigeria, Guinea, Madagascar, Burkina Faso, Benin, Senegal, Gambia, Sierra Leone, and Malawi. Nigeria shows the largest relative reduction by .44 % for one additional heat day, or 21.8 % for a 1-SD increase (SD = 55.1, $p = .000$). This translates into a large absolute reduction by .95 visits to 3.39 expected visits from the mean of 4.3 visits. A small subset of countries shows significant increases: Gabon, Timor-Leste, and Bolivia. Among these, Gabon showed the largest relative increase by 76.3 % for an additional 35°C day ($p = .000$). But since variation in 35°C days is low (SD = 0.02), the resulting increase by 1.42 % or .07 absolute visits for a 1-SD increase in 35°C days is comparatively small. The absolute increase in Bolivia is similar in magnitude (.08 fewer expected visits, $p = .000$).

Fig. 2: Temperature impacts on ANC visits in the pooled sample (**a**), India (b**),** Latin America and the Caribbean (**c**), Sub-Saharan Africa (**d**), Southeast and East Asia (**e**), and North Africa and West Asia (**f**). Coefficient estimates from a negative binomial for the effect of one additional day in the approximated gestational period in the respective temperature bin on the number of ANC visits for the pregnancy, translated into a percent change in expected visits. Panel (**g**) shows effect % changes in expected ANC visits by countries. Countries for the plot were selected based on a z-statistic greater than 1.75 and a confidence interval length of less than .01. For more information on the data and modelling, see **Data and Methods** section.

3.3 Socially stratified impacts of extreme heat on ANC visits across subpopulations

Socioeconomic factors stratify the adverse impact of extreme heat above 35°C on ANC utilization, and their analysis can highlight vulnerable subgroups of the population and relevant mechanisms across LMICs (**Fig. 3**). Mothers with no formal or only primary education show the largest relative reductions in ANC, compared to mothers with secondary or higher education (**Fig. 3a**). For them, ANC visits decline by .19 % for one additional >35°C day, resulting in an absolute change by .36 expected visits (or by 11.1 % for a 1-SD increase, SD = 58.9, p = .000). In comparison, secondary and higher educated mothers exhibit .09 % and .08 % fewer visits for an additional >35°C day (or 3.8 % and 3.3 % for a 1-SD increase, SD = 35.3 and 31.4). Indicators for economic attainment highlight that ANC reductions are only apparent for the lower country-specific wealth quintiles (**Fig. 3b**). Mothers from the top quintile (richest) show a non-significant increase in ANC under heat, indicating that they may be able to intensify ANC visits if heat-induced pregnancy complications occur. By contrast, the poorest mothers (bottom quintile) show no response to heat (p > .05). For poorer and richer mothers, expected ANC visits decrease by .11 % and .19 % for an additional 35°C day (or by 5.7% and 2.7 % for a 1-SD increase in 35°C days, i.e. .27 and .34 fewer expected visits). In line with this finding, mothers who report that getting money to visit a healthcare provider is a problem in accessing healthcare for them, also show ANC decreases – unlike mothers who report no such problems (**Fig. 3c**).

Fig. 3: Association between >35°C days and ANC visits by population subgroups across LMICs. Coefficient estimates from a negative binomial for the effect of one additional day in the approximated gestational period in the respective temperature bin on the number of ANC visits for the pregnancy, translated into a percent change in expected visits. Effect estimates are from separate regressions for each subsample. The regression includes further temperature bins and rainfall controls. Please refer to the **Data and Methods section** for information on data, variables, and modelling. For an overview of estimates as percent changes and absolute changes in expected visits for an additional >35°C day and for a 1-SD increase in >35°C days, please refer to **Appendix Table 2**.

Few differences by birth characteristics are apparent. There is a gradient in maternal age at birth, with mothers of higher maternal ages showing the relatively largest reduction in ANC visits for an additional >35°C day (**Fig. 3d**). While births of all birth orders show ANC reductions under heat, these are estimated to be largest for third and fourth births, in relative terms (**Fig. 3e**). Male and female infants exhibit very similarly sized reductions in ANC (**Fig. 3f**).

Accessibility of healthcare moderates heat impacts on ANC strongly. ANC reductions are detected in both urban and rural locations (**Fig. 3g**), but they are more pronounced in rural locations. In rural locations, an additional 35°C day reduces expected ANC visits by .18 % (or by .2 % or .33 expected visits for a 1-SD increase, SD = 54.6). While mothers in rural areas experience larger ANC reductions in relative terms, the reduction in expected ANC visits is similar across groups in absolute terms (.33 % and .32 visits). Mothers who report that they have problems in accessing healthcare because of the distance to the health facility (**Fig. 3h**), having to take transport (**Fig. 3i**), and not wanting to go alone (**Fig. 3j**) consistently exhibit reductions in ANC under heat exposure. These ANC reductions contrast with mothers who report facing no such problems and do not show ANC reductions in response to heat.

Health provider characteristics do not moderate the relationship between extreme heat and ANC in the pooled sample. Mothers who reported concerns regarding a lack of a female provider (**Fig. 3k**) or regarding any provider being available (**Fig. 3l**) show no ANC reductions under heat, like mothers who report no concerns. An exception is the relatively small negative effect for >35°C days for mothers who have small concerns that no female provider is available (-.07 % for a >35°C day, p = .004).

Indicators of female empowerment in household decision stratify heat impacts on ANC, too, although all subgroups have fewer ANC visits under heat (**Fig. 3m-r**). First, mothers who report that getting permission to go to access healthcare is a problem show substantial ANC reductions under heat, unlike mothers who report no such problems. For mothers who face problems getting permission, a 1-SD increase in 35°C days reduces expected ANC visits by .43 to .45 visits (or by 9.3 % and 11.8 %, SD = 51.1 and 54.2). Second, **Fig. 3m-r** show ANC responses to heat exposure by decision-making involvement. The groups include mothers who have the final say in household decision-making, those who jointly make these with the husband or other persons, and those who are not involved. When examining relative percent changes in response to heat, little differences appear between groups regarding decision-making on the respondent's healthcare, big purchases, how the husband's earnings should be used, and family visits. However, in absolute terms, mothers have substantially larger reductions in ANC visits if they are uninvolved in decision-making. These differences are apparent for having the final say on healthcare (.52 fewer expected visits for a 1-SD increase in >35°C days), daily purchases (.59), big purchases (.6), and the husband's earnings (.43), where ANC decreases are larger than in the respective comparison groups (alone or joint decision-making). The gap between uninvolved and involved mothers ranges from .3 to 1.3 expected visits and is largest for decision-making involvement in husband's earnings. These differences between relative and absolute changes are explained by two factors: Mothers who are not involved in decision-making have both systematically fewer ANC visits on average and live in locations with a higher standard deviation in >35°C days.

3.4 Socially stratified impacts of extreme heat in Sub-Saharan Africa and India

Sub-Saharan Africa shows similarly stratified patterns in ANC reductions under heat as the pooled sample (**Fig. 4**), but the negative effect of heat is larger here, both in relative and absolute changes (percent changes and changes in expected visits). None and primary educated mothers exhibit a .14 % (>35°C day) or a 14.4 % reduction (1-SD increase, SD = 68), resulting in absolute change by .43 expected visits, compared to .33 fewer expected visits for secondary and .22 for higher educated mothers. Mothers in the second, third, and fourth wealth quintile show statistically significant reductions, as opposed to mothers in the top quintile (richest). Reporting of getting money to go to a health facility as a small or big problem remains a strong stratifier of the heat impact, with .55 and .41 fewer expected visits for a 1-SD exposure increase (SD = 62.7 and 69.9) and no statistically significant change for those who report not facing such a problem. For infant birth order, Sub-Saharan Africa shows a gradient where reductions are largest for the second birth and decrease with advancing birth order.

In Sub-Saharan Africa, differences between rural and urban areas are stark both in relative and absolute terms (unlike in the pooled sample where they were more pronounced for relative changes), even though both groups show reductions. The reduction in rural areas by .22 % is more than twice as large as in urban areas (.11 %) for an additional heat day. Rural areas consequently are estimated to have .45 and urban areas .33 fewer expected ANC visits for a 1-SD increase in >35°C days (SD = 66.3 and 63.0). Relative responses to heat by distance to the health facility are similarly large between subgroups (-.22 % and -.23 % for a >35°C day). Absolute responses are larger for the group that reported distance as a big problem, with .54 fewer visits (SD = 63.6), as opposed to .47 fewer visits for those who report a small problem (SD = 64.3).

In Sub-Saharan Africa, concerns about whether a female provider is available were masked in the pooled sample (**Fig. 4k**). The group that reported small or big concerns shows reductions, while the group that reported no such concerns exhibits an increase in ANC visits by .15 % for an additional heat day (or .37 for a 1-SD exposure increase, SD = 59.7). In combination with the finding of stark differences between mothers who reported concerns around not wanting to go alone to a health facility (**Fig. 4j**), this suggests that social norms play an important role in shaping vulnerability to heat impacts during pregnancy. Mothers who report no concerns around going alone and the lack of female providers may be able to increase their ANC visits under heat exposure. The subsamples were too small to identify differences by concerns about whether any provider is available (**Fig. 4l**).

In terms of female involvement in decision-making, no clear gradient is apparent between subgroups that are more or less involved (**Fig. 4m-r**). An exception to this remains the disadvantage women face who report getting permission to go is a small or big problem in accessing healthcare (**Fig. 4m**). A >35°C day decreases ANC visits by .26 % and .24 % for these women (or 14.7 % and 14.3 % for a 1-SD increase, SD = 62.0 and 65.1). This leads to a reduction in expected ANC visits by .62 and .5 visits, as opposed to no statistically significant reduction for women who report no problem. The reduction is also large given the low sample means of only 4.2 and 3.5 visits. These reductions are among the largest absolute reductions for the Sub-Saharan African sample, besides the large decreases observed for certain birth order and maternal age groups.

Fig. 4: Association between >35°C days and ANC visits by population subgroups across DHS countries in Sub-Saharan Africa. Coefficient estimates from a negative binomial for the effect of one additional day in the approximated gestational period in the respective temperature bin on the number of ANC visits for the pregnancy, translated into a percent change in expected visits. Effect estimates are from separate regressions for each subsample. The regression includes further temperature bins and rainfall controls. Please refer to the **Data and Methods** section for information on data, variables, and modelling.

I find no evidence that the pooled sample for India (**Fig. 2b**) masked heterogeneities within the Indian population. As shown in **Fig. 5a-j** for a subset of samples where effect estimates were precisely estimated, none of the social groups show statistically significant responses in ANC visits to heat exposure.

Fig. 5: Association between >35°C days and ANC visits by population subgroups in India. Coefficient estimates from a negative binomial for the effect of one additional day in the approximated gestational period in the respective temperature bin on the number of ANC visits for the pregnancy, translated into a percent change in expected visits. Effect estimates are from separate regressions for each subsample. The regression includes further temperature bins and rainfall controls. Please refer to the **Data and Methods** section for information on data, variables, and modelling.

For other world regions (Latin America and the Caribbean, North Africa and West Asia, Central Asia, Southern and Eastern Europe), the analytical samples are too small to clearly identify heterogeneity in heat impacts on ANC by social groups. The PSU fixed effects are necessary to control for location-specific factors that are time constant, such as healthcare infrastructure and social norms. This is of particular importance in contexts where there are large within-sample inequalities in ANC, such as those shown in **Fig. 1a** for Latin America and the Caribbean, South and Southeast Asia, and North Africa. However, these fixed effects absorb substantial variation that limits further heterogeneity analysis. Please refer to **Table 1** for an overview of sample sizes for each world region.

4 Discussion

This study assessed the impact of temperature exposure during pregnancy on ANC visits across 52 LMICs with information on more than 860,000 births at more than 96,000 villages and city blocks. The findings provide insight into the effect of temperature at different intensities and particularly the effect of extreme heat (>35°C), while controlling for seasonality throughout the annual cycle on the subnational level, non-linearity of temperature intensity, annual trends on the subnational level, and location-specific factors on the village/city block level. The findings highlight inequities in the impact of extreme heat on ANC across world regions, countries, and social groups.

Extreme heat affects ANC visits disproportionately in the populations already most affected by the adverse impacts of global warming and the social groups most disadvantaged in accessing ANC. The analysis across world regions shows that reductions in ANC visits in response to >35°C days are most pronounced in Sub-Saharan Africa. In Sub-Saharan Africa, mothers in the sample have on average only 3.64 visits, significantly fewer than all other LMIC regions but on par with South and Southeast Asia (**Appendix Table 2**). Both across world regions and within Sub-Saharan Africa, the mothers that show the largest ANC reductions under heat have lower SES and face significant problems in generally accessing healthcare for themselves. This study underlines that an analysis of heterogeneous impacts across social groups can reveal differences in vulnerability that are masked in pooled samples.

The estimates in this study should be viewed in light of an increased need for ANC under extreme heat than at baseline. ANC may be critical in preventing heat-induced pregnancy complications, as extreme heat has been consistently associated with adverse maternal health and birth outcomes, such as preterm birth and stillbirth (Chersich et al. 2020; McElroy et al. 2022; Basu et al. 2010; Lakhoo et al. 2025). Some world regions and social groups show increases in ANC visits under extreme heat. In this context, ANC increases could indicate that some advantaged social groups are not only less affected by immobility under heat – they may even be able to intensify the ANC they receive when temperature is extreme. These increases are apparent in Latin America and the Caribbean and South and Southeast Asia, though small sample sizes prevented an analysis of heterogeneous impacts by social groups. Within Sub-Saharan Africa, mothers who report no concerns around going to a health facility alone or around the lack of a female provider show ANC increases in response to heat. This points to two further lines of inquiry. First, the determinants that shape ANC increases under heat should be explored in further studies, for example with information from health providers. Second, the role of ANC in buffering the impact of extreme heat on pregnancy health should be explicitly considered.

Some world regions showed no response to temperature during pregnancy. This includes India, where ANC visits were stable at any intensity and I did not identify underlying heterogeneous impacts between social groups either. In North Africa and West Asia, effect estimates were also not statistically significant, though consistently negative for all temperature bins (relative to the 20-25°C bin). As this geographic region faces extreme temperature increases in the coming decades because of climate change, further studies with extensive healthcare records should explore the effect of temperature on ANC here and investigate inequities between social groups.

Future studies should identify whether some social groups are adversely affected by heat, even in the contexts where my pooled analysis finds no or positive impacts of heat on ANC. In North Africa and West Asia, where I found no effect of heat, and in Latin America and the Caribbean and South and Southeast Asia, where I found increases, large inequities in ANC exist within these populations. These inequities could further shape vulnerability to heat that is masked in larger region and country level analyses. Interventions need to effectively address these vulnerable groups to make sure disadvantaged mothers are not further left behind. For analyses that can provide such insight, country level health records may serve as a useful data source.

This study underscores that expanding access to ANC remains a crucial priority for public health in LMICs and that global warming may impede necessary progress on this front in the most vulnerable populations of the world. Extreme heat in the future may lead to large reductions in ANC visits. In Sub-Saharan Africa, .58 fewer expected visits from an already low average of only 3.63 visits in the sample at baseline are observed for a 1-SD increase in >35 °C days during pregnancy. Especially factors that shape access to healthcare more generally determine accessibility of ANC under heat, pointing to the importance of policies aiming to improve both healthcare infrastructure and utilization. The disproportionate ANC reductions for mothers who are concerned about the lack of a female provider also show that health facility characteristics and social norms need to be considered in respective policies. In addition, policies that improve gender equality may have positive downstream effects on ANC. This is corroborated by my finding that ANC utilization under heat is shaped by mothers' ability to get permission to visit a facility as well as respondent's decision-making on their own healthcare and other household decisions.

This study has several limitations. First, this study focuses on the effects of absolute temperature, while controlling for precipitation in the gestational period. This is arguably meaningful given that there is a limit to human adaptability to extreme heat, which is surprisingly similar across diverse climates (Sherwood and Huber 2010). Nevertheless, future studies should explore whether humidity plays an important role in the effect of temperature on ANC utilization. Second, while this study investigates heterogeneous responses in heat impacts by social characteristics that can point to mechanisms, additional work is needed to test concrete pathways directly. Third, there may be important geographic, social, infrastructure, and economic determinants on the community and country level that shape the relationship between temperature and ANC and are not investigated here. Temperature could also disrupt service provision in health facilities and how this interacts with individual behaviour is underexplored to date. Hence, considering quality of care and services provided, beyond frequency of visits, will help paint a clearer picture of temperature impacts on prenatal care. Fourth, the study's fixed effects modelling approach requires a large sample size, which prevents the identification of country level effects and within country heterogeneity for many LMICs. This gap should be filled by additional studies with extensive data on ANC utilization.

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Appendix

Appendix Table 1: Overview of DHS surveys in the analytical sample

Country	DHS SurveyId	N (births) per survey	N (births) per country
Central Asia (N = 4,992)			
Armenia	AM2016DHS	1,182	1,182
Tajikistan	TJ2017DHS	3,810	3,810
India (260,217)			
India	IA2015DHS	133,245	260,217
	IA2020DHS	126,972	
Latin America and the Caribbean (N = 59,327)			
Bolivia	BO2008DHS	5,355	5,355
Colombia	CO2010DHS	10,745	10,745
Dominican Republic	DR2007DHS	7,012	7,012
Guyana	GY2009DHS	914	914
Haiti	HT2000DHS	3,550	10,561
	HT2006DHS	3,081	
	HT2016DHS	3,930	
Peru	PE2000DHS	8,848	24,740
	PE2004DHS	8,887	
	PE2009DHS	7,005	
North Africa & West Asia (N = 76,410)			
Egypt	EG1992DHS	7,849	53,404
	EG1995DHS	10,616	
	EG2000DHS	9,500	
	EG2003DHS	4,867	
	EG2005DHS	11,342	
	EG2008DHS	9,230	
Jordan	JO2002DHS	3,293	18,989
	JO2007DHS	5,461	
	JO2017DHS	6,435	
	JO2023DHS	3,800	

Morocco	MA2003DHS	4,017	4,017
South & South-east Asia (excl. India) (71,730)			
Bangladesh	BD2000DHS	3,813	17,855
	BD2004DHS	3,734	
	BD2007DHS	3,376	
	BD2017DHS	3,269	
	BD2022DHS	3,663	
Cambodia	KH2000DHS	5,594	15,137
	KH2005DHS	5,190	
	KH2021DHS	4,353	
Nepal	NP2001DHS	3,714	11,826
	NP2006DHS	3,128	
	NP2016DHS	2,909	
	NP2022DHS	2,075	
Philippines	PH2003DHS	3,587	16,880
	PH2008DHS	3,457	
	PH2017DHS	6,008	
	PH2022DHS	3,828	
Timor-Leste	TL2009DHS	5,630	10,032
	TL2016DHS	4,402	
Southern & Eastern Europe (N = 4,091)			
Albania	AL2008DHS	1,075	3,064
	AL2017DHS	1,989	
Moldova	MB2005DHS	1,027	1,027
Sub-Saharan Africa (N = 385,754)			
Angola	AO2015DHS	8,281	8,281
Benin	BJ1996DHS	2,454	12,815
	BJ2001DHS	2,874	
	BJ2017DHS	7,487	
Burkina Faso	BF1993DHS	4,701	21,492
	BF1999DHS	4,780	
	BF2003DHS	6,310	

	BF2021DHS	5,701	
Burundi	BU2016DHS	7,392	7,392
Cameroon	CM1991DHS	2,339	10,859
	CM2004DHS	3,878	
	CM2018DHS	4,642	
Central African Republic	CF1994DHS	2,263	2,263
Congo Democratic Republic	CD2007DHS	4,496	4,496
Cote d'Ivoire	CI1994DHS	3,089	7,958
	CI2021DHS	4,869	
Eswatini	SZ2006DHS	1,404	1,404
Ethiopia	ET2000DHS	6,371	18,551
	ET2005DHS	5,904	
	ET2016DHS	6,276	
Gabon	GA2019DHS	2,925	2,925
Gambia	GM2019DHS	4,460	4,460
Ghana	GH1993DHS	1,813	12,437
	GH1998DHS	2,632	
	GH2003DHS	2,170	
	GH2008DHS	1,607	
	GH2022DHS	4,215	
Guinea	GN2005DHS	3,697	8,407
	GN2018DHS	4,710	
Kenya	KE2008DHS	2,967	16,741
	KE2014DHS	5,326	
	KE2022DHS	8,448	
Lesotho	LS2004DHS	2,233	5,269
	LS2009DHS	1,999	
	LS2023DHS	1,037	
Liberia	LB2007DHS	2,618	6,173
	LB2019DHS	3,555	
Madagascar	MD1997DHS	3,072	18,264
	MD2008DHS	7,171	

	MD2021DHS	8,021	
Malawi	MW2000DHS	5,922	33,205
	MW2004DHS	5,608	
	MW2010DHS	10,872	
	MW2015DHS	10,803	
Mali	ML1996DHS	5,140	25,454
	ML2001DHS	6,724	
	ML2006DHS	8,040	
	ML2018DHS	5,550	
Mauritania	MR2020DHS	6,161	6,161
Mozambique	MZ2022DHS	4,585	4,585
Namibia	NM2000DHS	2,174	4,599
	NM2006DHS	2,425	
Niger	NI1992DHS	5,908	10,022
	NI1998DHS	4,114	
Nigeria	NG1990DHS	6,881	42,667
	NG2003DHS	3,065	
	NG2008DHS	13,855	
	NG2018DHS	18,866	
Rwanda	RW2005DHS	4,187	8,456
	RW2019DHS	4,269	
Senegal	SN1993DHS	4,176	19,864
	SN1997DHS	5,636	
	SN2005DHS	5,585	
	SN2023DHS	4,467	
Sierra Leone	SL2008DHS	2,557	7,902
	SL2019DHS	5,345	
South Africa	ZA2016DHS	2,256	2,256
Tanzania	TZ1999DHS	1,644	12,209
	TZ2015DHS	5,522	
	TZ2022DHS	5,043	
Togo	TG1998DHS	3,328	3,328

Uganda	UG2000DHS	2,244	12,170
	UG2006DHS	3,026	
	UG2016DHS	6,900	
Zambia	ZM2007DHS	2,833	14,357
	ZM2013DHS	6,468	
	ZM2018DHS	5,056	
Zimbabwe	ZW1999DHS	1,590	8,332
	ZW2005DHS	3,332	
	ZW2015DHS	3,410	

Appendix Table 2: Results for negative binomial regressions for each world region used for Fig. 2. For information on data, variables, and modelling, see “Data and methods” section.

World region	Temperature exposure (pregnancy)	Beta	SE	p-value	sign.	SD (exposure variable)	Mean ANC visits in sample	SD of ANC visits in sample	% change (for 1 additional day)	change (for 1 SD increase)	% change (for 1 SD increase)	Expected ANC (1 day)	Expected ANC (1 SD)	Abs. change in ANC (1 SD)
Pooled sample	<10°C day	-0.0004	0.00027	0.132	NA	18.65	4.18	3.91	-0.041	-0.008	-0.77	4.18	4.15	0.032
Pooled sample	10–15°C day	0.00002	0.00016	0.885	NA	27.28	4.18	3.91	0.002	0.001	0.06	4.18	4.18	-0.003
Pooled sample	15–20°C day	-0.0002	0.00021	0.313	NA	34.07	4.18	3.91	-0.021	-0.007	-0.73	4.18	4.15	0.03
Pooled sample	25–30°C day	0.00033	0.00016	0.045	*	69.89	4.18	3.91	0.033	0.023	2.33	4.18	4.27	-0.097
Pooled sample	30–35°C day	0.00022	0.00014	0.12	NA	57.56	4.18	3.91	0.022	0.013	1.29	4.18	4.23	-0.054
Pooled sample	>35°C day	-0.0023	0.00025	0	**	53.81	4.18	3.91	-0.228	-0.123	-11.56	4.17	3.69	0.483
Sub-Saharan Africa	<10°C day	-0.0028	0.00082	0.001	**	3.65	3.64	2.85	-0.279	-0.01	-1.02	3.63	3.6	0.037
Sub-Saharan Africa	10–15°C day	-0.0001	0.00062	0.819	NA	8.36	3.64	2.85	-0.014	-0.001	-0.12	3.64	3.64	0.004
Sub-Saharan Africa	15–20°C day	-0.0003	0.00033	0.426	NA	25.58	3.64	2.85	-0.026	-0.007	-0.66	3.64	3.62	0.024
Sub-Saharan Africa	25–30°C day	0.00051	0.0002	0.011	*	73.79	3.64	2.85	0.051	0.038	3.85	3.64	3.78	-0.14
Sub-Saharan Africa	30–35°C day	0.00014	0.00024	0.541	NA	61.83	3.64	2.85	0.014	0.009	0.9	3.64	3.67	-0.033
Sub-Saharan Africa	>35°C day	-0.0026	0.00027	0	**	65.51	3.64	2.85	-0.264	-0.173	-15.9	3.63	3.06	0.579
India	<10°C day	0.00038	0.00049	0.439	NA	24.58	4.38	4.81	0.038	0.009	0.93	4.38	4.42	-0.041
India	10–15°C day	0.00014	0.00064	0.821	NA	13.63	4.38	4.81	0.014	0.002	0.2	4.38	4.38	-0.009

India	15–20°C day	-0.0003	0.00028	0.352	NA	24	4.38	4.81	-0.026	-0.006	-0.62	4.37	4.35	0.027
India	25–30°C day	-0.0001	0.00019	0.591	NA	45.85	4.38	4.81	-0.01	-0.005	-0.46	4.38	4.36	0.02
India	30–35°C day	-0.0002	0.00018	0.303	NA	44.92	4.38	4.81	-0.019	-0.009	-0.85	4.37	4.34	0.037
India	>35°C day	-0.0002	0.00018	0.205	NA	38.94	4.38	4.81	-0.023	-0.009	-0.89	4.37	4.34	0.039
South & Southeast Asia	<10°C day	-0.001	0.001	0.333	NA	12.15	3.64	3.15	-0.097	-0.012	-1.17	3.64	3.6	0.043
South & Southeast Asia	10–15°C day	-7E-05	0.00088	0.937	NA	14.23	3.64	3.15	-0.007	-0.001	-0.1	3.64	3.64	0.004
South & Southeast Asia	15–20°C day	0.00011	0.00055	0.844	NA	25.06	3.64	3.15	0.011	0.003	0.27	3.64	3.65	-0.01
South & Southeast Asia	25–30°C day	0.00048	0.00019	0.013	*	83.97	3.64	3.15	0.048	0.04	4.13	3.64	3.79	-0.15
South & Southeast Asia	30–35°C day	0.00057	0.00023	0.013	*	74.96	3.64	3.15	0.057	0.043	4.36	3.64	3.8	-0.159
South & Southeast Asia	>35°C day	0.00187	0.00067	0.006	**	19.5	3.64	3.15	0.187	0.036	3.71	3.65	3.77	-0.135
North Africa & West Asia	<10°C day	-0.0006	0.00102	0.535	NA	6.41	4.91	5.05	-0.063	-0.004	-0.41	4.91	4.89	0.02
North Africa & West Asia	10–15°C day	-0.0006	0.00053	0.258	NA	20.09	4.91	5.05	-0.06	-0.012	-1.2	4.91	4.85	0.059
North Africa & West Asia	15–20°C day	-0.0012	0.00074	0.1	+	21.44	4.91	5.05	-0.122	-0.026	-2.59	4.9	4.78	0.127
North Africa & West Asia	25–30°C day	-0.0009	0.00044	0.054	+	19.86	4.91	5.05	-0.085	-0.017	-1.67	4.9	4.83	0.082
North Africa & West Asia	30–35°C day	-0.0007	0.00058	0.239	NA	24.61	4.91	5.05	-0.069	-0.017	-1.68	4.91	4.83	0.082
North Africa & West Asia	>35°C day	-0.0008	0.00052	0.134	NA	47.38	4.91	5.05	-0.078	-0.037	-3.63	4.9	4.73	0.178
Latin America & Caribbean	<10°C day	-0.0003	0.00025	0.193	NA	24.55	6.26	3.62	-0.032	-0.008	-0.78	6.26	6.21	0.049
Latin America & Caribbean	10–15°C day	-0.0003	0.00017	0.128	NA	84.46	6.26	3.62	-0.026	-0.022	-2.19	6.26	6.13	0.137
Latin America & Caribbean	15–20°C day	-0.0002	0.00018	0.307	NA	77.46	6.26	3.62	-0.019	-0.015	-1.44	6.26	6.17	0.09
Latin America & Caribbean	25–30°C day	0.00003	0.00032	0.928	NA	102.62	6.26	3.62	0.003	0.003	0.3	6.26	6.28	-0.019
Latin America & Caribbean	30–35°C day	0.00062	0.00032	0.056	+	65.16	6.26	3.62	0.062	0.04	4.11	6.27	6.52	-0.258

Latin America & Caribbean	>35°C day	0.00202	0.00092	0.028	*	4.19	6.26	3.62	0.202	0.008	0.85	6.28	6.32	-0.053
Central Asia	<10°C day	-0.0008	0.00144	0.583	NA	54.79	5.49	3.3	-0.079	-0.043	-4.23	5.48	5.25	0.232
Central Asia	10–15°C day	-0.0003	0.00124	0.844	NA	12.55	5.49	3.3	-0.025	-0.003	-0.31	5.48	5.47	0.017
Central Asia	15–20°C day	-0.0014	0.00081	0.091	+	15.1	5.49	3.3	-0.137	-0.021	-2.05	5.48	5.37	0.112
Central Asia	25–30°C day	-0.0028	0.0011	0.013	*	22.36	5.49	3.3	-0.275	-0.061	-5.96	5.47	5.16	0.327
Central Asia	30–35°C day	-0.0019	0.00119	0.114	NA	25.57	5.49	3.3	-0.187	-0.048	-4.67	5.48	5.23	0.256
Central Asia	>35°C day	-0.002	0.00137	0.14	NA	28.91	5.49	3.3	-0.202	-0.058	-5.67	5.47	5.17	0.311
Southern & Southeastern Europe	<10°C day	-0.0013	0.00147	0.375	NA	43.69	6.06	4.1	-0.13	-0.057	-5.52	6.05	5.72	0.334
Southern & Southeastern Europe	10–15°C day	0.00035	0.00202	0.861	NA	19.2	6.06	4.1	0.035	0.007	0.68	6.06	6.1	-0.041
Southern & Southeastern Europe	15–20°C day	-0.0012	0.00177	0.517	NA	15.81	6.06	4.1	-0.115	-0.018	-1.8	6.05	5.95	0.109
Southern & Southeastern Europe	25–30°C day	-0.0017	0.00128	0.182	NA	17.43	6.06	4.1	-0.17	-0.03	-2.93	6.05	5.88	0.177
Southern & Southeastern Europe	30–35°C day	0.00052	0.00207	0.8	NA	15.54	6.06	4.1	0.052	0.008	0.82	6.06	6.11	-0.049
Southern & Southeastern Europe	>35°C day	-0.0002	0.00398	0.959	NA	3.53	6.06	4.1	-0.02	-0.001	-0.07	6.05	6.05	0.004

Chapter IV: Temperature and sex ratios at birth

Empirical chapter 2

Co-authorship note: This chapter is based on co-authored work with Joshua Wilde[1, 2, 3, 4, 5], Anna Dimitrova[6], Ridhi Kashyap[1, 2, 7], Raya Muttarak[8]. I designed and conceptualized the research, cleaned the data, conducted all statistical analyses, made all figures and tables, and wrote the paper. Joshua Wilde and Raya Muttarak contributed to conceptualization. Anna Dimitrova downloaded the data and merged environmental and survey data. Raya Muttarak assisted during the journal review process.

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Chapter IV: Temperature and sex ratios at birth

Abstract: Human sex ratios at birth (SRBs) shape population composition and are closely linked to maternal health and gender discrimination. In the context of climate change, SRBs may theoretically be skewed by physiological or behavioural responses to exposure to global warming. However, evidence for this is limited. In this study, we estimate the effect of prenatal exposure to temperature on birth sex by linking survey data on 5 million live births in 33 sub-Saharan African countries and India with high-resolution temperature data. To distinguish between spontaneous and induced abortions, we exploit sociodemographic differentials, exposure timing, and regional differences in son preference. We find that days with a maximum temperature above 20°C are negatively associated with male births in both regions. In sub-Saharan Africa, we observe fewer male births after high first trimester temperature exposure, consistent with increased spontaneous abortions from elevated maternal heat stress. This is particularly true for births by mothers in rural areas, with little formal education, and for higher birth orders. By contrast, in India we find second trimester temperature exposure is associated with fewer male births, consistent with reductions in induced sex-selective abortions. As expected, these reductions are concentrated in higher birth orders and older mothers. We also find large reductions in male births by sonless mothers in northern Indian states, where son preference is greater. These findings demonstrate that climate change harms maternal health, increases prenatal mortality, and reduces engagement with the health system, leading to a complex effect on sex ratios at birth.

Significance Statement: While some evidence suggests sex ratios at birth are shaped by environmental and social factors, little is known about the relationship between temperatures and sex ratios. We show that high temperatures in the nine months before birth are negatively associated with male births in sub-Saharan Africa and India. The exposure timing demonstrates that climate change can increase prenatal mortality in early pregnancy, particularly among males, in both world regions. We also demonstrate that in regions with high son preference, elevated temperatures during windows where sex-selective abortions could take place reduce these abortions. These findings demonstrate that climate change may have complex behavioural and biological implications for maternal and fetal health, and ramifications on social phenomena such as gender discriminatory practices.

1 Introduction

Human sex ratios at birth[19] (SRBs) – or the ratio of male to female offspring – have been a fascination of social scientists from at least the 1600s (James 1987; Graunt 1962). Over the centuries, several explanations have been proposed and dismissed to explain SRB variations (James 1987). A consensus emerged in the mid-1900s that sex ratios at birth were likely constant, genetically determined, and invariant to social or environmental shocks (James 1987). However, since the 1970s new theoretical biological mechanisms were proposed by which social and environmental factors could affect SRBs, most notably via male in-utero fragility (Trivers and Willard 1973). This led to a re-emergence of research in this field

[19] The sex ratio at birth (the ratio of male to female offspring) is also referred to as the secondary sex ratio. The ratio of male to female offspring at conception is referred to as the primary sex ratio.

(Song 2012). At the same time, interest in SRBs increased dramatically among social scientists as ultrasound technology led to a rise in sex-selective abortion of girls in many countries in Asia and Eastern Europe, skewing SRBs significantly above their natural levels (Bongaarts and Guilmoto 2015; Chao et al. 2019).

Yet little attention has been given to the possible effects of climate change on SRBs. This is particularly puzzling given the renewed interest in social, environmental, and behavioural determinants of SRBs (Catalano et al. 2008; Hesketh and Xing 2006; Song 2012), and the growing literature on the effect of extreme heat on unintended pregnancy terminations via heat-induced in-utero mortality (Barreca et al. 2018; Cho 2020; Conte Keivabu et al. 2024; Hajdu and Hajdu 2020; 2021a; 2023; Marteleto et al. 2023), which is triggered by maternal heat stress. Given existing evidence on male in-utero fragility and heat-induced in-utero mortality, we ask whether the prenatal mortality effects of heat are male-biased, manifesting themselves in a skew in the SRB under climate change.

In this paper, we estimate the effect of ambient temperatures during conception and pregnancy on the sex ratio at birth[1]. To assess both biophysical health and behavioural mechanisms (see **Fig. 1**), we conduct a comparative analysis across two major world regions with vastly different experiences with son preference and sex-selective abortion. Specifically, we compare differences in the effect of temperature exposure between India and sub-Saharan Africa. In India, son preference is strong and sex-selective abortion of female pregnancies has led to male-skewed SRBs (Chao et al. 2019). By contrast, in sub-Saharan Africa there is little evidence of son preference and sex-selective abortion is considered minimal (Basu and De Jong 2010; Jayachandran and Pande 2017; Kashyap and Behrman

2020). To the best of our knowledge, this is the first large-scale study on the impact of temperatures during conception and pregnancy on human SRBs.

The sex ratio at birth (secondary sex ratio)[1] may respond to extreme temperature via a sex-biased prenatal mortality response after conception. Orzack et al. (Orzack et al. 2015) show that at conception, the sex ratio is balanced (0.5 proportion male). However, prenatal mortality introduces a sex-bias that shifts throughout pregnancy. Building on this study that provides fundamental insight into early human development, we investigate how prenatal mortality changes in response to a specific prenatal stressor (temperature). Gestational heat exposure threatens the maternal body's ability to thermoregulate, increasing the risk of pregnancy losses (Wesselink et al. 2024; Richards et al. 2022). Such pregnancy losses are triggered by fetal strain that can arise from dehydration, the diversion of blood and oxygen flow away from the placenta, hormonal dysregulation and inflammatory responses (Bonell et al. 2022; Yüzen et al. 2023). We hypothesize that these heat-induced pregnancy losses are male-biased, in line with Trivers and Willard's "frail male" hypothesis (1973). According to this evolutionary argument, weak males may have a lower chance of surviving to birth under poor environmental conditions. After birth, males have lower survival probabilities than females and thus require greater maternal investment (Mace and Sear 1997; Wells 2000). This makes frail male pregnancies not only costly for the mother but also less likely to yield further offspring. In consequence, to protect maternal resources and ultimately increase offspring, under environmental stress in-utero selection may be more pronounced for males.

Beyond direct physiological impacts of heat on pregnancy survival, there may be reproductive *behavioural* responses to heat, particularly in terms of induced abortion behaviour, that shape the SRB. To examine this vastly understudied behavioural mechanism, we exploit a comparison between India and sub-Saharan Africa. In most countries, an SRB of 103-107 boys to 100 girls is observed (Chao et al. 2019). In India, by contrast, the SRB is significantly male-skewed because of sex-selective abortion of female pregnancies, which are motivated by son preference. Particularly northern states in India have consistently shown highly inflated SRBs of around 116:100 in 2005-2016 (Bhat and Zavier 2003; Chao and Yadav 2019; Bhat and Zavier 2007). In southern states, which are not known for sex-selection, the SRB was estimated at around 107:100 (Singh et al. 2021). The intensity of son preference, and its manifestation in prenatal sex selection, are not only more dominant in northern states of India but also intensified at later birth orders and in families without sons (Aksan 2021; Arnold et al. 1998; Retherford and Roy 2004). High temperatures could impact abortion access through mobility disruptions (de Montigny et al. 2012; Saneinejad et al. 2012; Samano et al. 2021; Wu et al. 2021) and by increasing financial uncertainty and reducing income generation (Cui and Tang 2024; Aragón et al. 2018). Hence, we investigate heat effects on the probability of male birth for higher order births (four and higher) and between sonless mothers and mothers with at least one son between northern and southern states, and compare results to the sub-Saharan African placebo. We conduct this test for heat exposure in the second gestational trimester, as sex determination is reliable from approximately the 13th gestational week (Efrat et al. 1999; Odeh et al. 2009).

Fig. 1. Conceptual framework on health and behavioural mechanisms in response to temperature exposure before birth that may cause sex-specific mortality responses

Existing studies on the impact of temperatures on SRBs have several methodological limitations. These studies link annual temperature measurements to births on the country level (Catalano et al. 2008; Helle et al. 2008), which cannot a) adequately capture variation of exposures between subnational geographic areas, b) accurately map the temperature exposure at a location to the pregnancy duration of each birth on the micro-level, c) provide insight into the potential non-linearity of the temperature-sex relationship although different temperature thresholds might have varying impacts on the SRB, and d) account for seasonality in environmental exposures, parental selection into pregnancy, underlying parental health, and other proximate and distal factors. In addition, to identify environmental determinants of the SRB, sufficient variation within and across geographic units and seasons is necessary. This has led to inconsistent findings from small-scale single-country studies (Fukuda et al. 2014; Helle et al. 2008; Lerchl 1999) and a focus on high-income countries where large, high-quality register data is available. In the Global South, the link between temperatures and SRBs remains unexplored, despite populations' heightened vulnerability to the impacts of global warming.

We address these issues by pooling micro-level data on more than 5 million live births from 104 Demographic and Health Surveys (DHS) conducted between 2000 and 2022 in 33 sub-Saharan Africa countries and India. We link each georeferenced birth with gridded, high-resolution daily maximum temperature data for the approximate pregnancy period, using information on the month of birth. Our fixed-effect regressions estimate the impact of days with varying temperature intensity (below 15°C, 20-25°C, 25-30°C and above 30°C) in the three approximate pregnancy trimesters on the SRB in sub-Saharan Africa and India, while accounting for seasonality, non-linearity, all time-constant characteristics and time trends on the subnational regional level. To infer about specific mechanisms, we use the timing of exposure, sociodemographic differentials, and cultural differences in son preference between sub-Saharan Africa and India. Our study aims to provide insight into the relationship between temperatures and SRBs and the context-specific biological and behavioural determinants underpinning it.

2 Data and Methods

2.1 Birth and population data

We use population data from 104 georeferenced Demographic and Health Surveys (DHS) conducted between 2000 and 2022 in 33 sub-Saharan African countries and India (The DHS Program, n.d.). The DHS is an important source of information on health and wellbeing for low- and middle-income country populations, particularly women and children. It provides nationally representative cross-sectional data on women of reproductive age (ages 15-45), along with information on live births and maternal characteristics, such as educational attainment and age, among others.

For the purpose of this study, we use the DHS Births Recode files and include only those surveys and births where the primary sampling unit (PSU), defined as a grouping of households typically corresponding to a city block in an urban area or a village in a rural area, is georeferenced with latitude and longitude coordinates. For each live birth, its sex, month and year of birth are recorded. Using this information on the mother's place of residence and the child's time of birth, we extract high-resolution gridded climate data for each pregnancy for the month of its birth and the previous nine months to cover its gestational period. Though the clusters are displaced spatially by up to 10km to preserve respondents' anonymity, we link the climate data to the recorded PSU location as temperature values do not vary substantially on this scale. We restrict our sample to births by women aged 15-45 at childbirth who did not migrate in the year prior to the childbirth to address exposure misclassification bias. In total, we use 5,042,494 births

(3,053,730 in sub-Saharan Africa and 1,988,764 in India) from 1,631,831 women (***Appendix* Table 1**). The sample covers 381 administrative divisions on the first sub-national geographical level (i.e. state, province or equivalent) in sub-Saharan Africa, and 25 states in India (see ***Appendix* Table 2** for an overview of the surveys and samples).

The outcome variable is a binary indicator of whether the child born is male. The temperature exposure is based on the observed temperature at the mother's location for the approximate duration of the pregnancy for the respective child, making this a micro-level linkage for which the regression allows for inference on the sample level.

2.2 Climate Data

Temperature data was obtained from the National Oceanic and Atmospheric Administration's CPC Global Unified Temperature datasets (available at https://psl.noaa.gov/) (NOAA Physical Sciences Laboratory 2022). NOAA temperature data adjustments reflect well a global warming trend (Hausfather et al. 2016). These gridded data provide global coverage of surface temperatures, updated daily since 1979 and projected onto a 0.5 × 0.5 grid (ca. 55 km^2). For each day in the gestational period of a child, we extract the daily maximum temperature for the grid cell that intersects with the mother's cluster location.

2.3 Variables

Temperature exposure variables

We define the gestational period as the month of birth and the nine months prior to birth, to also include exposure around conception. The third trimester includes the month of birth and its three lags (1-month, 2-month, and 3-month lag), the second trimester the 4-month, 5-month, and 6-month lag, and the first trimester the 7-month, 8-month, and 9-month lag. To address autocorrelation, we also include the 10-month and 11-month lag. The treatment variables then are a vector of count variables that indicate for each gestational trimester of a live birth the number of days in the trimester with daily maximum temperatures that fall into a specified temperature bin (<15°C, 15-20°C, 20-25°C, 25-30°C, >30°C). This results in 15 treatment variables (five temperature bins for three gestational trimesters), of which we exclude the 15-20°C bins for each trimester from the regression as the reference category. The regression estimates the effect of one additional day in the given exposure trimester where the daily maximum temperature falls into the given 5°C temperature bin.

By using temperature bins, we allow the temperature-sex relationship to be non-parametric, following current best-practice methodology (Dell et al. 2014). For example, the effect of an additional >30°C heat day could differ from a 20-25°C heat day. In contrast to a cruder pregnancy exposure period, the trimester exposures provide more detailed insight into sensitive exposure timings, which we exploit to infer about mechanisms. We present results by trimester instead of monthly exposures to preserve statistical power, particularly in the heterogeneity analyses by maternal and birth characteristics (in ***Appendix*** **Table 4** we present main results on monthly exposures). As the DHS typically provide information only on the month of birth and not the exact day, except in more recent surveys, the exposures we construct an approximated the gestational period. In reality, however, gestational length may differ substantially across births, with preterm births making up an estimated 12.3 % of live births in sub-Saharan Africa in 2010 (Blencowe et al. 2012). The sample of surveys where day of birth information is available is too small to identify climatic SRB determinants with micro-level linkages in our empirical strategy, given the variation necessary within and across geographical units.

In alternative specifications (***Appendix* Figure S3**) we use relative exposure variables that are based on decile thresholds for each primary sampling unit's long-term temperature distribution from 1979 to 2022. While this approach may capture how extreme daily temperatures are given the temperature distribution usually observed at the specific location, the estimates mostly fail to reach statistical significance and do not provide more insight into the curve of the temperature-sex relationship than the used absolute thresholds (5°C bins).

Controls

In addition, we extract monthly precipitation gridded data from the Climatic Research Unit (CRU) at the University of East Anglia (Harris et al. 2020) to control for the total amount of rainfall at the PSU location measured in each approximate gestational month.

Effect modifiers

We examine heterogeneity in the temperature-sex relationship with DHS information on maternal and birth characteristics. This helps us test hypotheses on vulnerability to heat exposure and investigate mechanisms that explain sex ratio at birth variations. For each subgroup, we run a separate regression. We examine differences by the cluster location's urban-rural classification, formal educational attainment of the mother (none or primary; secondary or higher), maternal age at birth (ages 15-24; 25-29; 30+), and birth order (1; 2; 3; 4+). To investigate effects by sibling composition, we construct a binary variable that indicates for births of parity four and higher, whether the mother previously had a male live birth or not (sonless; at least one son). For India, we also examine difference between northern and southern states (the northern states include Bihar, Delhi, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, and Uttar Pradesh, after Kashyap and Behrman (2020)).

2.4 Estimation Strategy

We use a linear probability model with fixed effects to estimate the relationship between gestational heat exposure and birth sex in separate regressions for sub-Saharan Africa and India and each population subgroup (see **Effect Modifiers**). We employ a region-by-calendar-month-of-birth and a region-by-year-of-birth fixed effect, where the region refers to the first administrative unit on the subnational regional level (e.g. regions, states, etc.). For a child *i* born in subnational region *r* in month *m* in year *y*, the fixed-effects model for the effect of gestational temperature exposure on the child's sex (1=male) can be expressed as:

$$Male_{irmy} = \sum_{j}^{J} \sum_{k=0}^{K=11} \beta_k^j \, TEMPERATURES_{r,t-k}^{j} + rain_{rm} + \alpha_{rm} + \delta_{ry} + \varepsilon_{irmy} \qquad (1)$$

The outcome variable is a binary indicator of whether the child born is male. The temperature exposure is based on the observed temperature at the mother's location for the approximate duration of the pregnancy for the respective child. The temperature vector captures the daily maximum temperature distribution at the mother's cluster location, counting the number of days where the daily maximum temperature falls into the temperature bin *j* (<15°C, 15-20°C, 25-30°C, >30°C) in the pregnancy trimester (*t*-*k*, where *k*=0 up to 3). The regression yields one estimated coefficient for each temperature bin in each trimester. The effect of temperature exposure is estimated for each trimester individually (rather than cumulatively). Each coefficient indicates the effect of one additional day (i.e. a one-unit change) in the gestational trimester *k* where the temperature falls into the temperature bin *j*, relative to a 15-20°C day (as this bin is omitted from the regression as the reference category), on the probability of the born child being male. In the article, we additionally present the effect for a one standard deviation increase in the exposure variables to make results comparable across the samples for which we run the regressions separately.

The advantage of 5°C bins over summary (e.g., mean of daily temperature) and deviation (z-scores) measurements is that a separate estimate is derived for each temperature bin/intensity. This allows the model to capture non-linearity instead of assuming a linear relationship between heat exposure and the sex ratio. This is important as the effect of a hot >30°C day on the sex ratio may be different from a milder 20-25°C day, for example. By providing an individual estimate for the effect of temperature for each bin (heat intensity), the approach makes few assumptions about the biological significance of different thresholds. Therefore, the models can reveal the sensitive temperature ranges at which exposure affects the sex ratio. The underlying temperature distribution observed in our samples (which ranged from below 0°C to above 35°C) was divided into the specified bins to increase statistical power for below 15°C and above 30°C days. The use of 5°C bins is consistent with existing approaches and findings (Barreca et al. 2018; Conte Keivabu et al. 2024; Hajdu and Hajdu 2021b) and derived estimates can be used for projections. This approach is considered the best-practice methodology to capture non-parametric temperature impacts (Dell et al. 2014) and was first pioneered in the context of temperature impacts on fertility by Barreca et al. (2018).

$rain_{rm}$ is a control for the total amount of rainfall in each approximate gestational month (the month of birth and the preceding nine months). This control is included because temperature and rainfall may be correlated over time, as demonstrated in meterological studies that suggest temperature records should not be interpreted without considering its covariability with precipitation (Adler et al., 2008; Trenberth and Shea, 2005). Furthermore, rainfall could also impact the sex ratio at birth by having effects on maternal health through nutrition, income availability, infectious disease, and other factors brought about by rainfall levels that are also linked to humidity levels. Hence, we control for rainfall as a potential confounder of the temperature-sex relationship.

The region-by-month-of-birth fixed effect α_{rm} controls for region-specific seasonal patterns and other observed and unobserved factors that are constant within the month-region unit, as there can be substantial differences in seasonality, climatic conditions, population vulnerability, and sex ratios at births.

The estimation thus captures the effect of temperature differences on the outcome, given the location and time of the year. This fixed effect is key to our causal interpretation: It limits the temperature variation to fluctuations that occur across years (but within the same region and calendar month), making it plausibly random. The region-by-year-of-birth fixed effect δ_{ry} controls for annually time-varying factors on the subnational regional level. Alternatively, we explored region-year time trend instead of using single years, which yielded equivalent results. ε_{irmy} are the equation's error terms. This fixed effects approach requires sufficient variation between and within place-time units, which we achieve by pooling surveys across sub-Saharan Africa and India in our main specifications. Standard errors are clustered at the region level.

3 Results

Our analysis draws on two separate DHS samples of live births for sub-Saharan Africa[20] (N=3,053,730) and India (N=1,988,764) from 104 surveys at 59,087 primary sampling units (PSUs)[21]. The baseline SRB in sub-Saharan Africa is 50.84% male (103.42 males to 100 females), whereas in India the SRB is 52.5% (110.53 males to 100 females). The PSUs in sub-Saharan Africa and India exhibit similarly high daily maximum temperatures (the mean of the daily maximum temperature in the month of birth is 30.0°C in sub-Saharan Africa and 30.3°C in India), but more variation between clusters in India, where the standard deviation is 6.2 (sub-Saharan Africa 4.8). Heat days above >30°C are the most common of all the temperature ranges – at least 34% of all gestational days fall into this range in all trimesters across both samples. The maps in ***Appendix* Figure S1** show the dominant temperate, arid, and tropical climate zones in sub-Saharan Africa and India and the distribution of PSUs for the samples. Most births are by mothers who live in rural areas (73.4% in sub-Saharan Africa and 76.6% in India) with no or only primary level formal education (84.1% in sub-Saharan Africa and 61.06% in

[20] Angola, Burkina Faso, Benin, Burundi, Democratic Republic of Congo, Cote d'Ivoire, Cameroon, Ethiopia, Gabon, Ghana, Guinea, Kenya, Comoros, Liberia, Lesotho, Madagascar, Mali, Malawi, Mozambique, Nigeria, Niger, Namibia, Rwanda, Sierra Leone, Senegal, Swaziland, Chad, Togo, Tanzania, Uganda, South Africa, Zambia, Zimbabwe

[21] DHS samples are typically stratified by subnational regions (administrative level 1, e.g., province or states) and rural/urban areas. Within each strata, PSUs (clusters) are selected with probability proportional to size. In rural areas, a PSU refers to a village, and in urban areas to a city block, from which 25-30 households are then selected through equal probability sampling. The GPS information (latitude and longitude) provided for the PSU allows us to link high-resolution gridded climate data with the survey data on the cluster level.

India). The births are concentrated in parities three and higher in sub-Saharan Africa (56.5%) and in the first two parities in India (62.5%). Detailed descriptive statistics are in ***Appendix Table* 1** and an overview of surveys used in **Table 2.**

3.1 Temperature and sex ratios at birth in sub-Saharan Africa and India

Fig. 2 shows the results from two fixed effects linear probability models of the outcome of male birth on temperatures at different absolute thresholds in each gestational trimester, estimated separately for the sub-Saharan Africa and India sample (see Data and Methods). The coefficients indicate the change in the probability of the birth being male for an additional day in the trimester where the daily maximum temperature falls into the specified temperature range (bin) in reference to a 15-20°C day. The models control for region-specific seasonality and annual trends and shocks and exclude births by mothers who were not residents at the PSU location in the year prior to birth. Our results suggest that exposure to temperatures below 15°C and above 20°C is associated with decreases in male birth probability in both sub-Saharan Africa and India and these effects vary by trimester. Detailed results and effect changes as the change in the number of male births per 100 female births are available in ***Appendix* Table 3**.

Fig. 2. Associations between the number of days in the approximate gestational period that fall into a specified temperature bin and male birth, estimated separately for sub-Saharan Africa and India. Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate gestational trimester where the daily maximum temperature falls into the specified temperature bin. Panel A-C show the association between temperature exposure in each gestational trimester and male birth, Panel D shows the association for temperature exposure in the month nine months before the birth month. A detailed description of methods is available in ***Data and Methods***, and detailed results in ***Appendix* Tables 3-4**.

In the first trimester (**Fig. 2A**), the estimated coefficients for both sub-Saharan Africa and India all indicate a negative relationship between <15°C and >20°C temperature days and male birth probability, though they are only statistically significant for days above 20°C in sub-Saharan Africa. Here, an additional day in the first trimester with a daily maximum temperature of 20-25°C decreases the probability of male birth by .018 percentage points (or .33 percentage points for a 1-SD predictor change, SD=18.9, p=.035), a 25-30°C day by .019 percentage points (or .47 percentage points for a 1-SD predictor change, SD=24.6, p=.015), and a >30°C day by .017 percentage points (or .59 percentage points for a 1-SD predictor change, SD=34.7, p=.046).

Our analysis using monthly lags instead of trimester exposures indicates which approximate gestational months are sensitive to exposure *(*detailed results in ***Appendix* Table 4**). The results show that the first trimester reductions in sub-Saharan Africa appear particularly seven months before birth. The magnitude of effects is substantially larger in the analysis with aggregated trimester exposures, between -.052 percentage points for an additional 20-25°C day (or -.64 percentage points for a 1-SD predictor change, SD=6.7, p=.032) and -.051 percentage points for a 25-30°C day (or -.46 percentage points for a 1-SD predictor change, SD=9.1, p=.035).

While in the India sample, the analysis with trimester exposure does not show statistically significant first trimester effects, there are consistent male birth reductions for exposure around nine months before birth. For pregnancies with a standard duration of 40 weeks or nine months, the nine-month lag approximately corresponds to exposure around weeks one to four of gestation, but for shorter pregnancies the exposure might include conception[22].

In the second trimester, our results in **Fig. 2B** suggest substantial differences between sub-Saharan Africa and India. We do not identify temperature effects on birth sex in sub-Saharan Africa, where effects are very small and statistically insignificant (-.001 to .06 percentage points for a 1-SD change, p=.66; .84; .1; .85). However, in India, our results indicate a negative relationship between temperature exposure and birth sex. The effect of a 20-25°C is marginally statistically significant and indicates a lower male birth probability by .015 percentage points (or .24 percentage points for a 1-SD change, SD=15.8, p=.066)

[22] This is an approximation as most of the Demographic and Health Surveys we use do not include day of birth and gestational length information.

and by .017 percentage points for a 25-30°C day (or .34 percentage points for a 1-SD change, SD=19.6, p=.019).

Again, disaggregating trimester effects by monthly exposures (***Appendix* Table 4**), the second trimester male birth reductions in India appear to be driven by exposures six and five months before birth, with a magnitude of -.02 to -.46 percentage points for a 1-SD change in the predictor. By contrast, in the adjacent monthly lags – seven and four months before birth – temperatures across all bins indicate an insignificant weak and positive relationship. These findings are suggestive of a temperature response that is concentrated in a short and specific time window of six and five months before birth (or approximately 13 to 20 weeks of gestation for a standard pregnancy duration of 40 weeks or nine months[23]), with no response thereafter.

Fig. 2C shows that in the third trimester, negative temperature effects on male birth probability persist in India, but not in sub-Saharan Africa. One additional 25-30°C day in the third trimester decreases male births by .013 percentage points (or .3 percentage points for a 1-SD change, SD=23.7, p=.02). The other temperature bins fail to reach statistical significance but consistently suggest a negative relationship. Examining results for monthly exposures (***Appendix* Table 4**), the third trimester effects in India are driven particularly by exposure two months before birth. Two months before birth, a 20-25°C day is associated with a lower male birth probability by .034 percentage points (or .22 percentage points for a 1-SD change, SD=6.5, p=.042) and a 25-30°C day with a .037 percentage points reduction (or .31 percentage points for a 1-SD change, SD=8.37, p=.045).

[23] If exposure in the month of birth corresponds to gestational weeks 37 to 40, exposure nine months before birth should correspond to weeks one to four, eight months before birth to five to eight weeks of gestation, etc.

In sub-Saharan Africa, our results show statistically insignificant positive temperature effects.

Our findings reveal male birth reductions in response to heat in both sub-Saharan Africa and India, but sensitive time windows of gestational exposure differ between the two regions. Across neither sample do we find evidence of a gradient in the sex response by heat intensity, i.e. the magnitude of SRB reductions is not larger for hotter temperature days. However, once the temperature coefficients are translated into the effect for a 1-SD change in the exposure variable (instead of the effect for one additional day of the exposure variable), temperatures at higher intensity have larger effects on male birth probability. This means that since days of extreme heat intensity of 25-30°C and >30°C occur more frequently in the two pooled samples, such high intensities play an important role in shaping the sex ratio.

In addition, we find no evidence that geographic differences in the frequency of heat days significantly shape the curve of the temperature-sex relationship. While our models account for time-invariant differences between geographic regions with the use of region-level fixed effects, we test this specifically. For this purpose, we use alternative exposure variables reflecting PSU-specific relative thresholds that are based on deciles for each PSU's long-term temperature distribution from 1997 to 2022 (***Appendix* Figure S2**). These estimates fail to reach statistical significance. Hence, our findings suggest that the sex ratio at birth responds to temperature intensity in absolute terms consistently across geographic locations and that location-specific adaptation to extreme heat plays a minor role.

These findings are robust to the inclusion of mother fixed effects that control for all time-invariant health, social, cultural, geographic, financial and other factors that vary by the mother (***Appendix*** **Figure S3**).

3.2 Vulnerable population subgroups in sub-Saharan Africa

Based on our finding of a negative relationship between heat exposure in the first trimester and male birth in sub-Saharan Africa, we further investigate demographic heterogeneity in the temperature-sex relationship to identify vulnerable population subgroups. **Fig. 3** shows the results for first trimester temperature effects from a separate regression for each population subgroup by the rural/urban classification of the cluster location, maternal educational attainment and age at birth, and the child's birth order. The results suggest that different sociodemographic factors may shape vulnerabilities to cold and heat exposure in sub-Saharan Africa (for results for India, see ***Appendix*** **Figure S4**).

Fig. 3. Associations between the number of days in the approximate first trimester that fall into a specified temperature bin and male birth in Sub-Saharan Africa, estimated separately for each sociodemographic subgroup. Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate first trimester where the

daily maximum temperature falls into the specified temperature bin. The panels show the association between temperature exposure in the first gestational trimester and male birth for births in urban/rural classifications of the cluster of the mother's residence (Panel A), for births by mothers with no or primary and secondary or higher educational attainment (Panel B), for births by mothers at different completed maternal ages at birth (Panel C), and by birth order (Panel D). A detailed description of methods is available in ***Data and Methods***.

Fig. 3A indicates that births by mothers residing in rural areas have a lower probability of being male in response to cold and hot temperatures. A 20-25°C day in the first trimester is associated with a .028 percentage point decrease in male birth probability (or .54 percentage points for a 1-SD change, SD=19.3, p=.004) and a 25-30°C day with a .03 percentage point decrease (or .72 percentage points for a 1-SD change, SD=24.6, p=.001). The estimates for >30°C days and <15°C also show a decline but are not statistically significant. For urban areas, we observe a non-significant and very small positive relationship for temperatures above 20°C, suggesting that temperatures do not affect the SRB in urban areas.

Fig. 3B compares temperature effects between births by mothers with no or primary education and by those with secondary or higher education, showing that only the former group exhibits a lower male birth probability. Mothers with no or primary educational attainment show male birth reductions by .028 percentage points for a 20-25°C day (or .52 percentage points for a 1-SD change, SD=18.7, p=.005), by .031 percentage points for a 25-30°C day (or .75 percentage points for a 1-SD change, SD=24.3, p=.001), and by .028 percentage points for a >30°C day (or .98 percentage points for a 1-SD change, SD=35.18, p=.005). Again, the estimate for <15°C days also indicates a negative relationship but is not statistically significant (p=.281). By contrast, we detect no relationships between temperatures and birth sex for births by mothers with secondary or higher education.

Fig. 3C shows that we find no remarkable difference in the temperature-sex relationship by maternal age at birth. While for all age groups the temperature effect estimates indicate a negative relationship with male births or, for the ages above 30 years, a negligible positive relationship, none of the estimates are statistically significant.

The results by birth order in **Fig. 3D** indicate an inverse U-relationship, where the second parity has an increased probability of male birth under cold and hot days, but parities one as well as above three indicate decreases. These decreases are statistically significant for parities four and higher. They are less likely to be male by .046 percentage points for one 20-25°C day (or .84 percentage points for a 1-SD change, SD=18.4, p=.003), .041 percentage points for one 25-30°C day (or .99 percentage points for a 1-SD change, SD=24.4, p=.004), and .037 for one >30°C day (or 1.28 percentage points for a 1-SD change, SD=34.7, p=.016). These results suggest larger temperature effects on the SRB in high parity births.

In supplementary analysis using the Köppen-Geiger climate zone classification, we find that these first trimester reductions in Sub-Saharan Africa are more pronounced in tropical climate zones than in arid and temperate climate zones (***Appendix* Figure S5**).

3.3 Prenatal sex-selection responses in India

Next, we examine heterogeneities in the temperature-sex relationship in the second trimester in India analogously for the same sociodemographic characteristics as for the first trimester in sub-Saharan Africa, using a separate regression for each subgroup (**Fig. 4**).

Fig. 4. Associations between the number of days in the approximate second trimester that fall into a specified temperature bin and male birth in India, estimated separately for each sociodemographic subgroup. Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate second trimester where the daily maximum temperature falls into the specified temperature bin. The panels show the association between temperature exposure in the second gestational trimester and male birth for births by mothers with no or primary and secondary or higher educational attainment (Panel A), for births by mothers at different completed maternal ages at birth (Panel B), by birth order (Panel C), and for sonless mothers and mothers with at least 1 previous male birth in northern/southern states of India (Panel D). A detailed description of methods is available in ***Data and Methods***.

First, while we find no differences in SRB responses between urban and rural locations (see ***Appendix SI*****, Figure S6**), we find that births from mothers with little formal education are less male-biased (**Fig. 4A**). Only births from mothers with no or primary formal education have a lower SRB in response to heat, as opposed to births by mothers with at least secondary education, where we observe no change. The effects for days with a maximum temperature above 20°C range from -.021 to -.035 percentage points for one additional heat day (or -.4 and -.55 percentage points for a 1-SD change, SD=15.7, p-values <.03).

Furthermore, we find that births of parities four and higher and from mothers of maternal ages above 30 years are significantly less likely to be male. **Fig. 4B** shows that for birth order four and higher, male birth probability is reduced by .061

percentage points for a 20-25°C day (or 1.0 for a 1-SD change, SD=16.4, p=.002), .052 percentage points for a 25-30°C day (or.96 percentage points for a 1-SD change, SD=18.5, p=.001), and .044 percentage points for a >30°C day (or 1.45 percentage points for a 1-SD change, SD=32.9, p=.027). As presented in **Fig. 4C**, births with maternal ages above 30 are less likely to be male by .056 to .099 percentage points for a day above 20°C (or 1.19 to 1.87 percentage points for a 1-SD change, p-values <.01). For lower parities and maternal ages, we do not observe an association between temperatures and SRBs.

Next, we test whether the second-trimester SRB reductions in India are driven by determinants of sex-selective induced abortion practices in India. Culturally, a preference for sons over daughters and its manifestations have been shown to be stronger in northern states of India (Dyson and Moore 1983; Jayachandran and Pande 2017; Kashyap and Behrman 2020). In addition, sex-selective abortion is practiced particularly by women who already have multiple children but no or few male children among them yet (Aksan 2021; Arnold et al. 1998; Retherford and Roy 2004).

Based on these determinants of sex-selective induced abortion prevalence among the Indian population, we additionally test the temperature-sex relationship across four categories (in a separate regression for each): Focusing on births of parities four and higher, we compare births by sonless mothers with births by mothers who previously had at least one male birth, in both northern and southern states[24]. We find a mostly insignificant but strong association between temperatures and SRBs for births by sonless mothers in the North, and no association for the other groups.

[24] Category of northern states: Bihar, Delhi, Gujarat, Haryana, Himachal Pradesh, Jammu and Kashmir, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, and Uttar Pradesh, after Kashyap and Behrman (2020).

For births by sonless mothers in the North, we observe a large reduction in male birth probability by .183 percentage points for a 20-25°C day (or 2.77 percentage points for a 1-SD change, SD=15.2, p=.035). For the other temperature ranges, the effect estimates are similarly large (.147 and .123 percentage points) but fail to reach statistical significance (p=.091 and .167). For comparison, the temperature effect sizes are more than three times larger in this subgroup than the parity differentials we observed in sub-Saharan Africa.

By contrast, SRBs by mothers with at least one previous male birth in the South – potentially the least likely to induce sex-selective abortion – do not respond to temperatures (p>0.3). Similarly, we identify no impact of temperatures on the SRBs by sonless mothers in the South, and mothers with at least one son in the North.

Contrasting these results with analogous models for sub-Saharan Africa as the placebo, we identify no second-trimester temperature-sex relationship in any of the subgroups by these maternal and child characteristics (see ***Appendix SI*****, Figure S7**). Although the coefficients are not statistically significant, their direction is the opposite pattern compared to India: Instead of a decrease in male births as seen in India, in sub-Saharan Africa, we observe an increase in the probability of male births among mothers with no/primary education, of higher parity, older maternal age, and those who have not had a prior male birth.

The negative impact of heat on male birth probability in the second trimester is most pronounced in the arid climate zones of India (***Appendix*** **Figure S8**).

4 Discussion

We present evidence that temperatures before birth are associated with sex ratios at birth. Our results show a negative relationship between temperatures above >20°C and SRBs (i.e. fewer male births relative to female births) in both sub-Saharan Africa and India. However, we find substantive differences between the two regions. In sub-Saharan Africa, heat in the first trimester decreases the SRB. The decreases are driven by births of mothers who reside in rural locations, have none or primary formal education, and are concentrated in birth orders of four and higher. In India, by contrast, where sex-selective induced abortions against girls because of son preference have led to a significant male-skew in SRBs (Chao et al. 2019), we find that heat in the second trimester decreases SRBs. Here, reductions are driven by high parities and high maternal age births. In addition, we find some indication that large SRB decreases occur in births of parities four and higher by sonless mothers in northern states of India.

Our findings indicate that both biological health responses and behavioural responses explain SRB reductions under heat. In sub-Saharan Africa we explore social vulnerabilities to heat exposure that may be driven by direct physiological impacts on either conception or pregnancy survival (Barreca et al. 2018; Conte Keivabu et al. 2024; Hajdu and Hajdu 2021a; 2023). In addition, it is also likely that indirect health and behavioural mechanisms, such as temperature impacts on agricultural productivity and income generation, disease, and nutrition play a role (Cui and Tang 2024; Grace et al. 2021; Aragón et al. 2018). As information on gestational length is only available in the more recent DHS, we are not able to disentangle whether temperatures are linked with a lower male conception probability under heat or intensified in-utero mortality, but our analysis of monthly exposures points to the latter. The suggestive evidence we find for male birth reductions being most pronounced in tropical zones of sub-Saharan Africa is consistent with the idea that high humidity may play a role in shaping the relationship between heat and birth sex by decreasing the body’s ability to thermoregulate. In India, the concentrated timing of the shock (approx. 13th gestational week onwards), the heterogeneity pattern by sociodemographic characteristics, the magnitude of the effects observed for subgroups of the Indian population, and the cultural differences in son preference between India and sub-Saharan Africa suggest that fewer sex-selective induced abortions against girls take place when temperatures are above 20°C, resulting in a lower SRB. The male birth reductions in India are most accentuated in arid zones, where extreme temperature may make households particularly vulnerable to income insecurity from agricultural production losses (Rachunok and Fletcher 2023; Fernández et al. 2023), impacting their ability to afford abortions in private clinics.

The significant variations in SRBs following exposure to high temperatures, influenced by factors such as the mother's education, rural or urban residence, high parity, and advanced maternal age, indicate that these population subgroups are particularly vulnerable to heat stress. Our findings lend support to the Trivers-Willard hypothesis, which suggests that under adverse conditions during pregnancy – such as wars, terrorist attacks, and natural disasters – mothers are more likely to give birth to girls rather than boys (Trivers and Willard 1973). Although the evidence regarding the impact of maternal socioeconomic characteristics on SRBs remains mixed (Pennington et al. 2023; Takikawa and Fukukawa 2024), the skewed SRB observed among certain subgroups implies that mothers with lower levels of education who live in rural areas, for example, may have a reduced capacity to cope with extreme heat. As a result, they may struggle to protect their vulnerable male fetuses in-utero.

This study indicates that substantively large variations in SRBs are linked with temperature and reveals the curve of the temperature-sex relationship. The effect sizes of our results are large, given typical SRB variations both between and within populations over time (Chao et al. 2019). Further, our study uncovers which temperature intensities the sex ratio is sensitive to. The findings demonstrate that the sex ratio is less male for temperature above 20°C and that the sex difference in the response to heat remains stable at increased heat intensity. SRBs vary even at low levels of heat intensity, indicating that even moderately high temperatures may constitute heat stress for the maternal body and lead to behavioural responses that result in substantial changes in the SRB. At the same time, days of high heat intensity of 25-30°C and >30°C occur more frequently in our samples than moderately hot days, meaning that higher temperatures have a relatively larger impact on the SRB. Further, our results suggest that specific temperature intensities in *absolute* terms may shape the sex ratio at birth consistently across geographic locations. This is in line with evidence indicating that peak heat stress is surprisingly similar across diverse climates today (Sherwood and Huber 2010). Our sample has little variation in <15°C days, preventing us from identifying associations between cold temperatures and SRBs, indicated in previous literature using data on the Global North (Catalano et al. 2008).

This study has several limitations. Firstly, the lack of information on gestational length may lead to exposure misclassification and prevent us from differentiating conception and in-utero mortality channels, a line of inquiry hitherto unexplored.

Second, there may be other climatic exposures that moderate the effect of temperature. While we include rainfall controls, future studies may explore the role of humidity, crop yields and other environmental factors in explaining SRB variations.

Overall, this study demonstrates that there is a sex-specific response to temperatures before birth driven by both biological and behavioural responses that lead to substantial impacts on reproduction and population composition. We invite scientists to further explore the potential role of moderating environmental influences, factors that buffer and increase vulnerability to exposure, and the specific direct and indirect mechanisms that link temperatures with SRBs.

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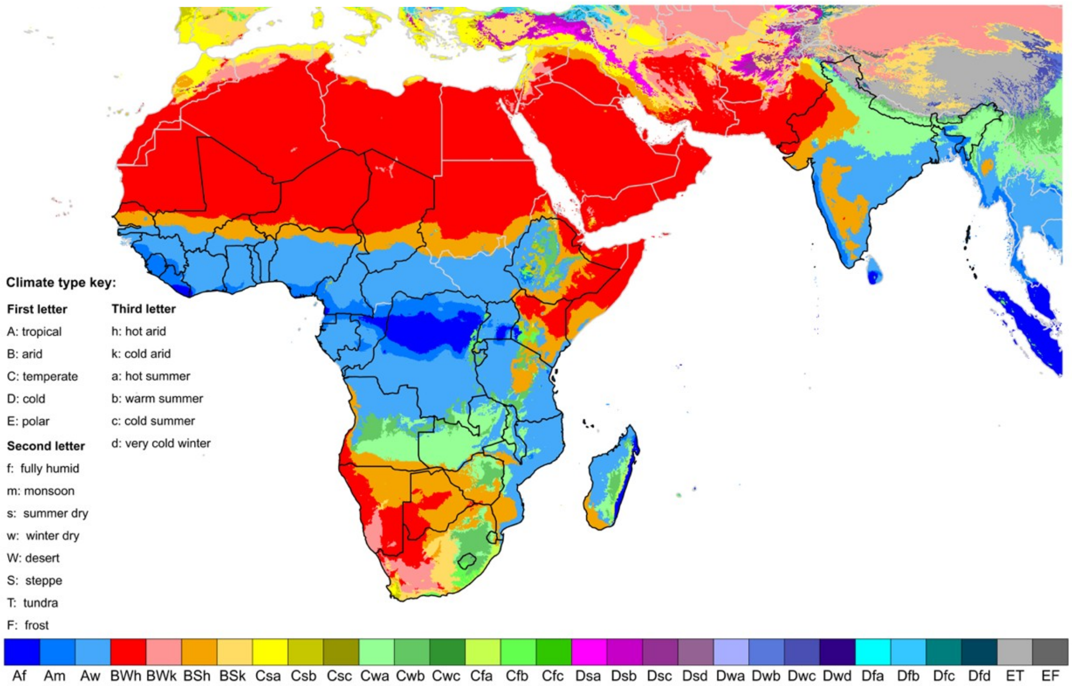
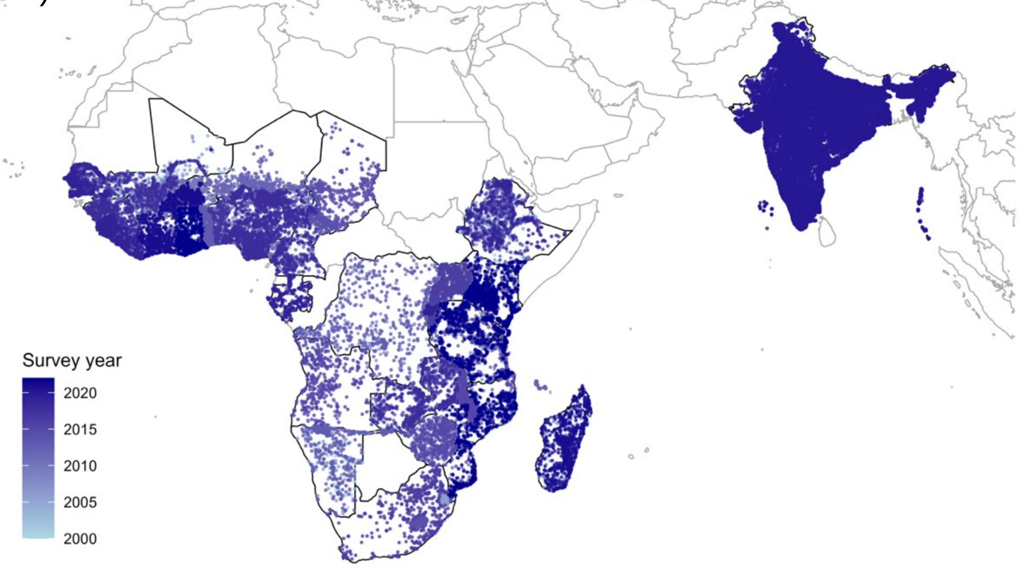
Appendix

Appendix Figure 1

A. Köppen-Geiger climate zones



B. Primary sampling unit locations (Demographic and Health Surveys 2000-2021)



Appendix Fig. 1: Coverage of Köppen-Geiger climate zones (Panel A) and location of the primary sampling units included in the sample from the Demographic and Health Surveys in Sub-Saharan Africa and India in 2000-2021 (Panel B).

Appendix Figure 2

A

B

C

Appendix Fig. 2: Associations between the number of days in the approximate trimester that fall into a specified relative temperature bin and male birth from separate regressions for sub-Saharan Africa and India. Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate trimester where the daily maximum temperature falls into the specified temperature bin. The percentile thresholds are defined based on each primary sampling unit's long-term daily maximum temperature distribution over the years 1979–2022. The panels show the association between temperature exposure for each gestational trimester. A detailed description of methods is available in ***Materials and Methods***.

Appendix Figure 3

A

B

C

Appendix Fig. 3. Associations between the number of days in the approximate trimester that fall into a specified temperature bin and male birth, estimated separately for Sub-Saharan Africa and India. Fixed effects include a mother fixed effect in addition to subnational region-by-month-of-birth and region-by-year-of-birth fixed effects. Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate trimester where the daily maximum temperature falls into the specified temperature bin. The panels A-C show the association between temperature exposure for each gestational trimester. A detailed description of methods is available in ***Materials and Methods***.

Appendix Figure 4

Appendix Fig. 4: Associations between the number of days in the approximate first trimester that fall into a specified temperature bin and male birth in India by sociodemographic characteristics.

Appendix Figure 5

A

B

C

Appendix Fig. 5. Associations between the number of days in each approximate trimester that fall into a specified temperature bin and male birth in Sub-Saharan Africa, estimated separately for each climate zone (Köppen-Geiger classification). Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate second trimester where the daily maximum temperature falls into the specified temperature bin. The panels show the association between temperature exposure in the first (Panel A), second (Panel B), and third (Panel C) gestational trimester and male birth for births in the climate zone classification of the cluster of the mother's residence. Number of observations by climate zone: Tropical N=578,851, Arid N=301,792, Temperate N=212,782. A detailed description of methods is available in ***Materials and Methods***.

Appendix Figure 6

Appendix Fig. 6: Associations between the number of days in the approximate second trimester that fall into a specified temperature bin and male birth in India by urban/rural classification of the cluster where the mother is resident.

Appendix Figure 7

Appendix Fig. 7: Associations between the number of days in the approximate second trimester that fall into a specified temperature bin and male birth in sub-Saharan Africa by sociodemographic characteristics.

Appendix Figure 8

A

B

C

Appendix Fig. 8. Associations between the number of days in each approximate trimester that fall into a specified temperature bin and male birth in India, estimated separately for each climate zone (Köppen-Geiger classification). Coefficients (dots) indicate the change in the probability of the birth being male, with 95% CIs (lines), for one additional day in the approximate second trimester where the daily maximum temperature falls into the specified temperature bin. The panels show the association between temperature exposure in the first (Panel A), second (Panel B), and third (Panel C) gestational trimester and male birth for births in the climate zone classification of the cluster of the mother's residence. Number of observations by climate zone: Tropical N=560,486, Arid N=375,469, Temperate N=887,554. A detailed description of methods is available in ***Materials and Methods***.

Appendix Table 1: Summary statistics (Data source: Demographic and Health Surveys 2000-2021)

Variable	Frequency (Proportion)/ Mean (SD)	
Births & Mothers	**Sub-Saharan Africa**	**India**
Total births (N)	3,053,730	1,988,764
Male births	1,553,795 (50.88 %)	1,041,566 (52.37 %)
Female births	1,499,935 (49.12 %)	947,198 (47.63 %)
Mothers	835,333	796,498
Temperature exposure		
Daily maximum (month of birth)	29.96°C (4.78)	30.33°C (6.18)
1st trimester below 15°C days	0.41 (3.21)	2.12 (10.44)
1st trimester 15-20°C days	2.43 (6.70)	3.77 (8.77)
1st trimester 20-25°C days	13.09 (18.77)	11.08 (16.13)
1st trimester 25-30°C days	31.16 (24.54)	24.07 (19.30)
1st trimester above 30°C days	44.22 (34.74)	50.27 (32.60)
2nd trimester below 15°C days	0.41 (3.21)	2.39 (11.42)
2nd trimester 15-20°C days	2.45 (6.75)	3.67 (8.65)
2nd trimester 20-25°C days	12.89 (18.68)	10.86 (15.98)
2nd trimester 25-30°C days	30.22 (24.39)	23.66 (19.34)
2nd trimester above 30°C days	45.29 (34.89)	50.66 (32.59)
3rd trimester below 15°C days	0.57 (4.23)	3.21 (14.61)
3rd trimester 15-20°C days	3.30 (8.73)	4.83 (10.63)
3rd trimester 20-25°C days	17.25 (24.45)	14.04 (19.47)
3rd trimester 25-30°C days	39.57 (31.06)	30.23 (23.37)
3rd trimester above 30°C days	60.96 (45.85)	69.52 (41.06)
Maternal Age		
15-24 years	1,562,144 (51.16 %)	1,189,271 (59.80 %)
25-29 years	742,565 (24.32 %)	537,727 (27.04 %)
30+ years	749,021 (24.53 %)	261,766 (13.16 %)
Birth order		
1st births	696,866 (22.82 %)	600,680 (30.20%)
2nd births	631,514 (20.68 %)	641,567 (32.26%)
3rd births	511,862 (16.76 %)	377,683 (18.99%)
4th and higher births	1,213,488 (39.74%)	368,834 (18.55%)
Education		
No education	1,563,665 (51.21 %)	896,865 (45.10 %)
Primary education	1,002,984 (32.84 %)	317,416 (15.96 %)
Secondary/higher education	486,921 (15.94 %)	774,483 (38.94 %)
Missing	160 (0.01 %)	0 (0.00%)
Urban/Rural		
Rural	2,241,808 (73.41 %)	1,901,336 (76.64%)
Urban	811,922 (26.59 %)	579,650 (23.36%)
Northern and southern states (India)		
Northern states	–	833,855 (41.93 %)
Southern states	–	1,154,909 (58.07 %)
Survey and geographic information		
Total number of surveys	102	2
Total number of countries	33	1
Subnational administrative	48	25

regions (GEO-LEV1)		
DHS clusters	2,269	56,818

Appendix Table 2: Overview of Demographic and Health Surveys used in the analysis

Country	DHS Survey ID	Obs. in sample	Percent of pooled sample
Angola	AO2011MIS	21,193	0.69
	AO2015DHS	40,611	1.33
Burkina Faso	BF2003DHS	32,368	1.06
	BF2010DHS	52,019	1.70
	BF2021DHS	40,793	1.34
Benin	BJ2001DHS	14,086	0.46
	BJ2012DHS	45,438	1.49
	BJ2017DHS	43,398	1.42
Burundi	BU2010DHS	24,209	0.79
	BU2016DHS	44,790	1.47
Democratic Republic of Congo	CD2007DHS	22,514	0.74
	CD2013DHS	52,765	1.73
Cote d'Ivoire	CI2012DHS	26,111	0.86
	CI2021DHS	38,491	1.26
Cameroon	CM2004DHS	18,707	0.61
	CM2011DHS	39,869	1.31
	CM2018DHS	31,848	1.04
Ethiopia	ET2000DHS	36,448	1.19
	ET2005DHS	32,736	1.07
	ET2011DHS	41,972	1.37
	ET2016DHS	38,657	1.27
	ET2019DHS	21,403	0.70
Gabon	GA2012DHS	21,729	0.71
	GA2019DHS	12,939	0.42
Ghana	GH2003DHS	9,900	0.32
	GH2008DHS	7,307	0.24
	GH2014DHS	22,084	0.72
	GH2022DHS	23,034	0.75
Guinea	GN2005DHS	22,214	0.73
	GN2012DHS	26,422	0.87
	GN2018DHS	27,751	0.91
Kenya	KE2008DHS	14,593	0.48
	KE2014DHS	67,477	2.21
	KE2022DHS	57,329	1.88
Comoros	KM2012DHS	10,609	0.35
Liberia	LB2007DHS	14,523	0.48
	LB2009MIS	8,477	0.28

Appendix Table 3: Main regression (trimesters)

Variable	Trim	Beta	SE	p	SD of variable in sample	Beta*SD	Baseline SRB (% male)	SRB (% male) + Beta	Baseline SRB (males: 100 females)	SRB after 1-SD change (males to 100 females)	Difference in male births per 100 females
Sub-Saharan Africa (N= 3337873, Adjusted R2=0.0002)											
<15°C day	(3)	-0.00009	0.00018	0.607	4.35	-0.00041	50.84%	50.80%	103.42	103.25	-0.169
<15°C day	(2)	-0.00010	0.00022	0.660	3.31	-0.00032	50.84%	50.81%	103.42	103.29	-0.132
<15°C day	(1)	-0.00005	0.00023	0.842	3.34	-0.00016	50.84%	50.82%	103.42	103.35	-0.064
20-25°C day	(3)	0.00010	0.00007	0.154	24.50	0.00249	50.84%	51.09%	103.42	104.45	1.037
20-25°C day	(2)	0.00002	0.00009	0.844	18.73	0.00032	50.84%	50.87%	103.42	103.55	0.133
20-25°C day	(1)	-0.00018	0.00008	0.035	18.85	-0.00334	50.84%	50.51%	103.42	102.04	-1.373
25-30°C day	(3)	0.00006	0.00007	0.350	31.18	0.00191	50.84%	51.03%	103.42	104.21	0.793
25-30°C day	(2)	0.00000	0.00008	0.998	24.48	-0.00001	50.84%	50.84%	103.42	103.41	-0.003
25-30°C day	(1)	-0.00019	0.00008	0.015	24.63	-0.00467	50.84%	50.37%	103.42	101.50	-1.914
>30°C day	(3)	0.00012	0.00007	0.085	45.76	0.00563	50.84%	51.40%	103.42	105.77	2.356
>30°C day	(2)	0.00002	0.00009	0.848	34.82	0.00062	50.84%	50.90%	103.42	103.67	0.257
>30°C day	(1)	-0.00017	0.00009	0.046	34.67	-0.00594	50.84%	50.25%	103.42	100.99	-2.427
India (N= 2,480,555, Adjusted R2= 0.0007)											
<15°C day	(3)	-0.00016	0.00009	0.079	14.55	-0.00231	52.50%	52.27%	110.53	109.51	-1.017
<15°C day	(2)	-0.00015	0.00011	0.166	11.37	-0.00171	52.50%	52.33%	110.53	109.77	-0.755
<15°C day	(1)	-0.00010	0.00011	0.337	10.35	-0.00107	52.50%	52.39%	110.53	110.05	-0.473
20-25°C day	(3)	-0.00009	0.00007	0.202	19.24	-0.00175	52.50%	52.32%	110.53	109.75	-0.775
20-25°C day	(2)	-0.00015	0.00008	0.066	15.76	-0.00241	52.50%	52.26%	110.53	109.46	-1.064
20-25°C day	(1)	-0.00009	0.00008	0.259	15.92	-0.00151	52.50%	52.35%	110.53	109.86	-0.666
25-30°C day	(3)	-0.00013	0.00005	0.020	23.65	-0.00300	52.50%	52.20%	110.53	109.20	-1.323
25-30°C day	(2)	-0.00017	0.00007	0.019	19.62	-0.00341	52.50%	52.16%	110.53	109.03	-1.501
25-30°C day	(1)	-0.00006	0.00007	0.427	19.53	-0.00110	52.50%	52.39%	110.53	110.04	-0.485
>30°C day	(3)	-0.00006	0.00006	0.335	40.94	-0.00240	52.50%	52.26%	110.53	109.47	-1.056
>30°C day	(2)	-0.00012	0.00008	0.160	32.44	-0.00383	52.50%	52.12%	110.53	108.84	-1.684
>30°C day	(1)	-0.00004	0.00007	0.579	32.45	-0.00130	52.50%	52.37%	110.53	109.95	-0.58

Appendix Table 4: Main regression (monthly lags)

Variable	Exposure month	Beta	SE	p	SD of variable in sample	Beta*SD	Baseline SRB (% male)	SRB (% male) + Beta	Baseline SRB (males: 100 females)	SRB after 1-SD change (males to 100 females)	Difference in male births per 100 females
Sub-Saharan Africa (N= 1,977,013, Adjusted R2=0.0006)											
<15°C day	lag0	0.00038	0.65000	0.513	1.20	0.00045	50.9%	50.9%	103.54	103.73	0.19
<15°C day	lag1	-0.00025	-0.43000	0.668	1.22	-0.00030	50.9%	50.8%	103.54	103.42	-0.13
<15°C day	lag2	-0.00008	-0.13000	0.895	1.23	-0.00010	50.9%	50.9%	103.54	103.50	-0.04
<15°C day	lag3	-0.00060	-1.01000	0.315	1.22	-0.00074	50.9%	50.8%	103.54	103.24	-0.31
<15°C day	lag4	0.00000	0.00000	0.997	1.19	0.00000	50.9%	50.9%	103.54	103.54	0.00
<15°C day	lag5	0.00004	0.06000	0.955	1.18	0.00004	50.9%	50.9%	103.54	103.56	0.02
<15°C day	lag6	-0.00018	-0.29000	0.775	1.18	-0.00022	50.9%	50.8%	103.54	103.45	-0.09
<15°C day	lag7	0.00025	0.39000	0.700	1.18	0.00029	50.9%	50.9%	103.54	103.66	0.12
<15°C day	lag8	0.00041	0.63000	0.530	1.18	0.00049	50.9%	50.9%	103.54	103.74	0.20
<15°C day	lag9	-0.00119	-1.78000	0.075	1.19	-0.00142	50.9%	50.7%	103.54	102.95	-0.59
<15°C day	lag10	0.00054	0.80000	0.425	1.20	0.00065	50.9%	50.9%	103.54	103.81	0.27
<15°C day	lag11	-0.00026	-0.44000	0.663	1.20	-0.00031	50.9%	50.8%	103.54	103.41	-0.13
20-25°C day	lag0	0.00026	1.15000	0.252	6.70	0.00172	50.9%	51.0%	103.54	104.26	0.71
20-25°C day	lag1	-0.00006	-0.26000	0.794	6.71	-0.00043	50.9%	50.8%	103.54	103.36	-0.18
20-25°C day	lag2	0.00024	0.98000	0.326	6.71	0.00158	50.9%	51.0%	103.54	104.20	0.66
20-25°C day	lag3	0.00015	0.60000	0.549	6.69	0.00097	50.9%	51.0%	103.54	103.95	0.40
20-25°C day	lag4	-0.00023	-0.94000	0.346	6.66	-0.00152	50.9%	50.7%	103.54	102.92	-0.63
20-25°C day	lag5	0.00011	0.48000	0.633	6.66	0.00076	50.9%	50.9%	103.54	103.86	0.32
20-25°C day	lag6	0.00012	0.49000	0.622	6.68	0.00079	50.9%	50.9%	103.54	103.87	0.33
20-25°C day	lag7	**-0.00052**	**-2.14000**	**0.032**	**6.69**	**-0.00345**	**50.9%**	**50.5%**	**103.54**	**102.12**	**-1.42**
20-25°C day	lag8	-0.00013	-0.54000	0.589	6.71	-0.00090	50.9%	50.8%	103.54	103.17	-0.37
20-25°C day	lag9	0.00001	0.06000	0.951	6.73	0.00010	50.9%	50.9%	103.54	103.58	0.04
20-25°C day	lag10	-0.00006	-0.26000	0.796	6.73	-0.00042	50.9%	50.8%	103.54	103.37	-0.17
20-25°C day	lag11	-0.00022	-0.94000	0.345	6.72	-0.00151	50.9%	50.7%	103.54	102.92	-0.62
25-30°C day	lag0	0.00008	0.37000	0.710	9.02	0.00073	50.9%	50.9%	103.54	103.85	0.30
25-30°C day	lag1	-0.00001	-0.05000	0.961	8.98	-0.00010	50.9%	50.9%	103.54	103.50	-0.04
25-30°C day	lag2	0.00028	1.16000	0.245	8.95	0.00249	50.9%	51.1%	103.54	104.58	1.04
25-30°C day	lag3	0.00004	0.16000	0.871	8.94	0.00035	50.9%	50.9%	103.54	103.69	0.15
25-30°C day	lag4	-0.00008	-0.33000	0.739	8.95	-0.00073	50.9%	50.8%	103.54	103.24	-0.30
25-30°C day	lag5	0.00003	0.13000	0.895	9.01	0.00028	50.9%	50.9%	103.54	103.66	0.12
25-30°C day	lag6	0.00006	0.27000	0.790	9.04	0.00058	50.9%	50.9%	103.54	103.78	0.24
25-30°C day	lag7	**-0.00051**	**-2.11000**	**0.035**	**9.06**	**-0.00460**	**50.9%**	**50.4%**	**103.54**	**101.65**	**-1.89**
25-30°C day	lag8	-0.00008	-0.33000	0.744	9.10	-0.00071	50.9%	50.8%	103.54	103.25	-0.29
25-30°C day	lag9	-0.00010	-0.44000	0.660	9.11	-0.00095	50.9%	50.8%	103.54	103.15	-0.39
25-30°C day	lag10	0.00005	0.20000	0.843	9.11	0.00044	50.9%	50.9%	103.54	103.72	0.18
25-30°C day	lag11	-0.00028	-1.20000	0.228	9.08	-0.00256	50.9%	50.6%	103.54	102.49	-1.06
>30°C day	lag0	0.00016	0.66000	0.511	12.24	0.00191	50.9%	51.1%	103.54	104.34	0.79
>30°C day	lag1	-0.00003	-0.13000	0.896	12.23	-0.00041	50.9%	50.8%	103.54	103.37	-0.17
>30°C day	lag2	0.00041	1.60000	0.109	12.24	0.00502	50.9%	51.4%	103.54	105.64	2.10
>30°C day	lag3	0.00005	0.21000	0.837	12.24	0.00065	50.9%	50.9%	103.54	103.81	0.27
>30°C day	lag4	-0.00014	-0.55000	0.580	12.20	-0.00175	50.9%	50.7%	103.54	102.82	-0.72
>30°C day	lag5	0.00010	0.39000	0.696	12.20	0.00118	50.9%	51.0%	103.54	104.03	0.49
>30°C day	lag6	0.00010	0.39000	0.698	12.16	0.00121	50.9%	51.0%	103.54	104.04	0.50
>30°C day	lag7	**-0.00045**	**-1.78000**	**0.076**	**12.14**	**-0.00550**	**50.9%**	**50.3%**	**103.54**	**101.29**	**-2.25**
>30°C day	lag8	-0.00015	-0.58000	0.561	12.17	-0.00181	50.9%	50.7%	103.54	102.79	-0.75
>30°C day	lag9	0.00006	0.26000	0.798	12.20	0.00078	50.9%	50.9%	103.54	103.86	0.32
>30°C day	lag10	0.00008	0.29000	0.769	12.26	0.00094	50.9%	51.0%	103.54	103.93	0.39
>30°C day	lag11	-0.00024	-0.98000	0.329	12.24	-0.00298	50.9%	50.6%	103.54	102.31	-1.23
India (N=2,981,905, Adjusted R2=.0002)											
<15°C day	lag0	-0.00028	0.00032	0.380	3.86	-0.00109	52.37%	52.3%	109.95	109.47	-0.48
<15°C day	lag1	0.00017	0.00029	0.547	4.02	0.00070	52.37%	52.4%	109.95	110.26	0.31
<15°C day	lag2	-0.00056	0.00032	0.082	4.16	-0.00233	52.37%	52.1%	109.95	108.93	-1.02
<15°C day	lag3	-0.00008	0.00031	0.793	4.21	-0.00035	52.37%	52.3%	109.95	109.80	-0.15

<15°C day	lag4	-0.00015	0.00027	0.575	4.18	-0.00064	52.37%	52.3%	109.95	109.67	-0.28
<15°C day	lag5	-0.00038	0.00031	0.220	4.12	-0.00155	52.37%	52.2%	109.95	109.27	-0.68
<15°C day	lag6	-0.00001	0.00033	0.970	4.04	-0.00005	52.37%	52.4%	109.95	109.93	-0.02
<15°C day	lag7	0.00018	0.00029	0.521	3.94	0.00072	52.37%	52.4%	109.95	110.27	0.32
<15°C day	lag8	-0.00015	0.00030	0.619	3.77	-0.00057	52.37%	52.3%	109.95	109.70	-0.25
<15°C day	lag9	-0.00041	0.00029	0.169	3.66	-0.00148	52.37%	52.2%	109.95	109.30	-0.65
<15°C day	lag10	0.00008	0.00031	0.793	3.62	0.00029	52.37%	52.4%	109.95	110.08	0.13
<15°C day	lag11	-0.00045	0.00040	0.265	3.68	-0.00166	52.37%	52.2%	109.95	109.22	-0.73
20-25°C day	lag0	-0.00004	0.00018	0.818	6.51	-0.00027	52.37%	52.3%	109.95	109.83	-0.12
20-25°C day	lag1	0.00003	0.00020	0.862	6.57	0.00022	52.37%	52.4%	109.95	110.05	0.10
20-25°C day	lag2	**-0.00034**	**0.00017**	**0.042**	**6.54**	**-0.00221**	**52.37%**	**52.1%**	**109.95**	**108.98**	**-0.97**
20-25°C day	lag3	-0.00006	0.00020	0.761	6.53	-0.00039	52.37%	52.3%	109.95	109.78	-0.17
20-25°C day	lag4	-0.00016	0.00018	0.383	6.53	-0.00105	52.37%	52.3%	109.95	109.49	-0.46
20-25°C day	lag5	**-0.00004**	**0.00020**	**0.859**	**6.56**	**-0.00023**	**52.37%**	**52.3%**	**109.95**	**109.85**	**-0.10**
20-25°C day	lag6	**-0.00034**	**0.00018**	**0.061**	**6.67**	**-0.00228**	**52.37%**	**52.1%**	**109.95**	**108.95**	**-1.00**
20-25°C day	lag7	0.00006	0.00017	0.727	6.73	0.00040	52.37%	52.4%	109.95	110.13	0.18
20-25°C day	lag8	0.00005	0.00018	0.788	6.65	0.00032	52.37%	52.4%	109.95	110.09	0.14
20-25°C day	lag9	-0.00036	0.00021	0.086	6.55	-0.00236	52.37%	52.1%	109.95	108.92	-1.03
20-25°C day	lag10	0.00000	0.00017	0.979	6.51	-0.00003	52.37%	52.4%	109.95	109.94	-0.01
20-25°C day	lag11	-0.00038	0.00016	0.017	6.45	-0.00245	52.37%	52.1%	109.95	108.88	-1.08
25-30°C day	lag0	-0.00018	0.00018	0.337	8.22	-0.00145	52.37%	52.2%	109.95	109.31	-0.64
25-30°C day	lag1	-0.00001	0.00019	0.939	8.24	-0.00012	52.37%	52.4%	109.95	109.90	-0.05
25-30°C day	lag2	**-0.00037**	**0.00018**	**0.045**	**8.34**	**-0.00310**	**52.37%**	**52.1%**	**109.95**	**108.60**	**-1.36**
25-30°C day	lag3	-0.00014	0.00020	0.471	8.34	-0.00119	52.37%	52.3%	109.95	109.43	-0.52
25-30°C day	lag4	0.00016	0.00019	0.389	8.35	0.00135	52.37%	52.5%	109.95	110.55	0.60
25-30°C day	lag5	**-0.00028**	**0.00020**	**0.162**	**8.37**	**-0.00232**	**52.37%**	**52.1%**	**109.95**	**108.93**	**-1.02**
25-30°C day	lag6	**-0.00042**	**0.00020**	**0.039**	**8.39**	**-0.00355**	**52.37%**	**52.0%**	**109.95**	**108.40**	**-1.55**
25-30°C day	lag7	0.00012	0.00019	0.511	8.37	0.00102	52.37%	52.5%	109.95	110.40	0.45
25-30°C day	lag8	0.00007	0.00019	0.714	8.38	0.00060	52.37%	52.4%	109.95	110.22	0.26
25-30°C day	lag9	-0.00031	0.00023	0.189	8.35	-0.00257	52.37%	52.1%	109.95	108.82	-1.13
25-30°C day	lag10	-0.00004	0.00019	0.830	8.25	-0.00033	52.37%	52.3%	109.95	109.81	-0.14
25-30°C day	lag11	-0.00021	0.00017	0.214	8.27	-0.00176	52.37%	52.2%	109.95	109.18	-0.77
>30°C day	lag0	-0.00005	0.00021	0.818	12.37	-0.00060	52.37%	52.3%	109.95	109.69	-0.27
>30°C day	lag1	-0.00002	0.00022	0.935	12.45	-0.00023	52.37%	52.3%	109.95	109.85	-0.10
>30°C day	lag2	-0.00023	0.00021	0.280	12.46	-0.00288	52.37%	52.1%	109.95	108.69	-1.26
>30°C day	lag3	-0.00018	0.00022	0.419	12.47	-0.00224	52.37%	52.1%	109.95	108.97	-0.98
>30°C day	lag4	0.00031	0.00022	0.161	12.41	0.00381	52.37%	52.8%	109.95	111.64	1.69
>30°C day	lag5	**-0.00037**	**0.00022**	**0.091**	**12.40**	**-0.00461**	**52.37%**	**51.9%**	**109.95**	**107.94**	**-2.01**
>30°C day	lag6	**-0.00030**	**0.00022**	**0.186**	**12.44**	**-0.00368**	**52.37%**	**52.0%**	**109.95**	**108.34**	**-1.61**
>30°C day	lag7	0.00024	0.00022	0.266	12.43	0.00300	52.37%	52.7%	109.95	111.28	1.33
>30°C day	lag8	0.00012	0.00022	0.571	12.40	0.00152	52.37%	52.5%	109.95	110.63	0.67
>30°C day	lag9	-0.00046	0.00025	0.062	12.32	-0.00568	52.37%	51.8%	109.95	107.48	-2.47
>30°C day	lag10	-0.00014	0.00022	0.528	12.32	-0.00168	52.37%	52.2%	109.95	109.21	-0.74
>30°C day	lag11	-0.00008	0.00019	0.666	12.31	-0.00102	52.37%	52.3%	109.95	109.50	-0.45

Chapter V: Survival of the fittest: How prenatal heat exposure reduces infant mortality in Mali

Empirical chapter 3

Co-authorship note: This chapter is based on co-authored work with Liliana Andriano[1] as second author. I conceptualized the research, developed the framing, downloaded the environmental data, merged it with the survey data, cleaned the data, conducted all statistical analyses, made all figures and tables, and wrote the paper. Liliana Andriano contributed to the conceptualization of the research and provided writing edits.

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Chapter V: Survival of the fittest: How prenatal heat exposure reduces infant mortality in Mali

Abstract: Environmental shocks in the prenatal period can have long-lasting consequences for health and wellbeing. Despite the substantial risks that extreme heat can pose for maternal and neonatal health, the consequences of heat exposure in the prenatal period for postnatal outcomes and the underlying mechanisms remain poorly understood. In this study, we provide a conceptual framework on mechanisms that could explain how prenatal heat exposure impacts infant mortality in low- and middle-income contexts and test these mechanisms empirically. We focus on the case of Mali, where seasonal trends provide an opportunity to analyze the impact of heat as a distinct environmental determinant of infant mortality. Linking data from the 2018 Mali Demographic and Health Survey with fine-resolution measures of heat conditions across the gestational period, we show that infants exposed to extreme heat in the second and third gestational trimester exhibit a lower risk of mortality. We find evidence suggesting that prenatal heat exposure increases in-utero mortality, which likely results in a cohort of newborns that are positively selected on health. We instead find no evidence that the reduction in the risk of infant mortality is driven by behavioural factors. Our findings contribute to a better understanding of the relationship between environmental determinants and early life outcomes, suggesting that heat-induced prenatal selection may shape the health and composition of future cohorts.

1 Introduction

Days of extreme heat are occurring more frequently, throughout prolonged periods, and at higher intensities because of climate change (IPCC 2023). In response to this, a growing demographic body of literature has emerged to investigate the impact of extreme temperatures on human populations, ranging from migration, fertility and mortality, to human capital and health outcomes (Barreca et al. 2018; Cho 2017; Dell et al. 2014; Gasparrini & Armstrong 2011; McMichael et al. 2006; Patz et al. 2005). Importantly, extreme temperatures before birth can impact health at birth, increasing the risk of preterm birth, low birthweight and stillbirth (Andriano 2023; Deschenes et al. 2009; Grace et al. 2021). However, whether this negative effect of extreme heat during pregnancy on health at birth translates into poorer health outcomes in the first years of life remains unclear and evidence is limited.

The pregnancy period is a sensitive time window when environmental shocks can have significant consequences for the mother and her offspring, both in the short- and long-term (Almond & Currie 2011; Barker 1990). On the one hand, adverse conditions during the prenatal period are linked with both adverse birth outcomes (Bekkar et al. 2020; Chen et al. 2020; Torche & Villarreal 2014) and impaired development after birth, influencing how offspring fares in terms of health, physical and cognitive abilities, and even labor market outcomes and earnings (Barker, 1990; Case et al., 2005; Hong et al., 2021; Isen et al., 2017; Noghanibehambari & Fletcher, 2024). On the other hand, environmental stressors can also induce pregnancy losses that lead to the selection of a stronger cohort which exhibits better outcomes later in life (Bruckner & Catalano 2018; Nobles & Hamoudi 2019). Therefore, prenatal environmental exposures may not only affect populations in a socially stratified manner, but also shape social stratification (Torche & Nobles 2024).

Despite the growing body of literature on early life exposures, it remains poorly understood how prenatal heat exposure impacts health and wellbeing after birth, especially in the first years of life. Here, the emerging evidence is contradictory. On the one hand, evidence suggests that prenatal heat exposure increases neonatal and infant mortality (Dimitrova et al. 2024; Geruso & Spears 2018). On the other hand, Wilde et al. (2017) find that prenatal heat exposure leads to higher educational attainment and literacy during childhood. Based on the scarce existing evidence, it is unclear which mechanism is more dominant in shaping the health of cohorts – the *scarring* of offspring from the lasting effects of gestational heat stress, or the *culling* of offspring through heat-induced pregnancy losses that lead to a positively selected cohort that survived the prenatal shock.

In this article, we extend the literature on the consequences of prenatal environmental exposures for health outcomes after birth by investigating whether and how prenatal exposure to extreme heat impacts infant mortality and provide four theoretical and empirical contributions. First, we propose a conceptual framework that illuminates how exposure to heat stress might influence infant mortality and test these mechanisms empirically. While existing research has focused on identifying causal links between environmental shocks and health outcomes in infancy, the pathways underlying these relationships often remain unexplored (Grace et al. 2020; Hoffmann et al. 2024). Second, we shed light on the distinct implications of extreme heat as an environmental exposure, while previous studies have mostly focused on drought exposure (Flatø & Kotsadam 2014; Kudamatsu et al. 2012; Kumar et al. 2016). This is important as different climatic extremes may elicit distinct physiological and behavioural responses (Hoffmann et al. 2024), and shape patterns of vulnerability among the population in ways that are unique to the type of shock (Squires & Hartman 2013). Third, we move beyond previous studies that examine the impact of heat stress on infant mortality in cross-national contexts with diverse climatic conditions (Geruso & Spears 2018) by focusing on a country with seasonal trends that allow us to capture extreme heat as a distinct driver of infant mortality (Grace et al. 2021). Lastly, examining health outcomes in infancy provides new insights into early-life selection processes, which are otherwise obscured by the current literature's focus on outcomes in adulthood (Fishman et al. 2019; Isen et al. 2017; Wilde et al. 2017; for an overview see Brink et al. 2024).

To investigate the link between prenatal heat exposure and infant mortality, we link fine resolution gridded meteorological data with 9,016 live births from the 2018 Demographic

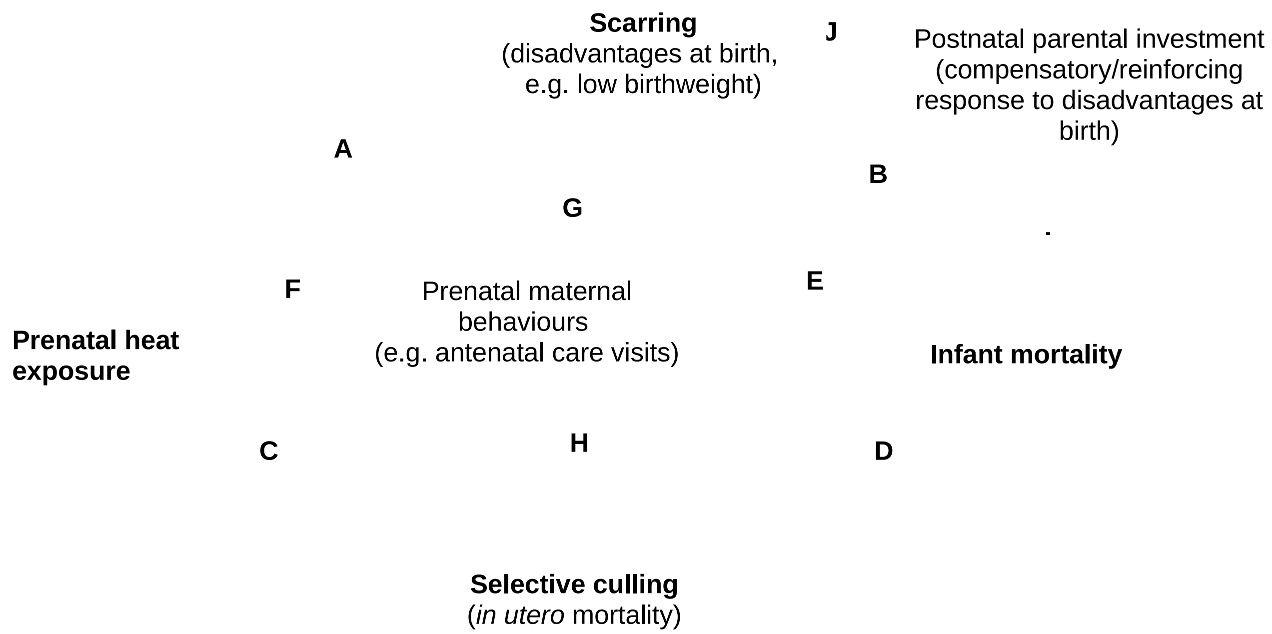
Health Survey in Mali. Our findings show that in-utero heat exposure in the second and third trimester decreases infant mortality. In additional analyses, we provide evidence supporting the theoretical expectation that increased in-utero mortality during heat conditions helps explain this effect. We find no evidence that the reduction in infant mortality is driven by lower access to antenatal care or compensatory maternal investment after gestational heat exposure. Our study offers novel evidence that prenatal heat exposure reduces infant mortality, most likely through intensified in-utero selection that dominates scarring effects and leads to a cohort with better survival chances. More broadly, this article provides further evidence that heat-induced selection in the prenatal period can shape the health and composition of new cohorts.

2 Conceptual framework

It is widely acknowledged that prenatal exposure to environmental shocks can significantly impact infant health and mortality through its effects on maternal stress, malnutrition, and an altered disease environment during pregnancy. Although the impacts of maternal malnutrition and an altered disease environment on infant mortality have been more extensively studied (Kudamatsu et al. 2012; Kumar et al. 2016; Rocha & Soares 2015), the specific effects of maternal heat stress during pregnancy on infant mortality have received little attention in the literature. In addition, previous studies examining the relationship between maternal heat stress and health outcomes have concentrated primarily on the physiological impacts of heat stress, with little attention paid to heat-induced behavioural changes that could impact infant mortality. To address these gaps in the literature on the impacts of maternal heat stress on infant mortality, we propose a conceptual framework that elucidates the physiological and behavioural pathways through which prenatal exposure to heat might influence infant mortality.

Drawing on existing literature, we hypothesize that prenatal heat exposure may influence infant mortality through competing mechanisms. We posit that a positive relationship between prenatal heat stress and infant mortality would be mediated by poorer birth outcomes such as low birthweight which is a well-known risk factor for infant mortality (Katz et al. 2013). Alternatively, a negative relationship between prenatal heat stress and infant mortality would be mediated by higher in-utero mortality which selects for healthier offspring who survive the prenatal shock. Beyond these physiological mechanisms, changes in infant mortality following prenatal heat exposure may also be influenced by behavioural factors. For instance, parents may compensate for heat-induced disadvantages at birth by increasing their investment in the child, and mothers may experience a lack of antenatal care during heat episodes that could pose a risk to maternal and fetal health. These physiological and behavioural mechanisms could operate simultaneously during the prenatal period (Bruckner & Catalano 2018) and after birth. By examining how infant mortality changes in response to prenatal heat exposure, we can determine which mechanism most influences health outcomes after birth. Below we further elaborate on these mechanisms and outline hypotheses that will guide our empirical investigation into the relationship between prenatal heat stress and infant mortality (**Figure 1**).

Figure 1: Conceptual framework on pathways through which prenatal heat exposure may impact infant mortality



2.1 Physiological pathways: Scarring and selective culling

Prenatal heat exposure may influence infant mortality by increasing the risk of adverse birth outcomes (Pathway A), which are associated with poorer health and development in infancy (Pathway B) – a phenomenon known as the scarring effect. Scholarship has shown that heat increases the risk of low birthweight (Andriano 2023; Conte Keivabu & Cozzani 2022; Grace et al. 2021), a major predictor of infant mortality (Katz et al. 2013). This effect of heat on birth outcomes is likely due to the physiological strain extreme heat places on pregnant women. Under high temperatures, the body triggers sweating to reduce heat, which can lead to dehydration and reduced blood and oxygen flow to the uterus and placenta (Yüzen et al. 2023). The resulting lack of placental blood and oxygen can affect the fetal heart rate, and result in fetal strain (Bonell et al. 2022). There is some evidence that heat-induced disadvantages in the prenatal period can manifest later in life in poorer adult health and socioeconomic attainment (Fishman et al. 2019; Isen et al. 2017; for an overview see Brink et al. 2024). If this scarring mechanism is more dominant, we would expect prenatal heat exposure to reduce health at birth and increase infant mortality. We hypothesize:

H1a: Prenatal heat exposure is negatively associated with health at birth.

H1b: Prenatal heat exposure is positively associated with infant mortality.

Alternatively, extreme heat in the prenatal period may reduce infant mortality by selecting out the most vulnerable fetuses during gestation (Pathways C and D). This selection process, which we refer to as selective culling, posits that extreme heat could increase fetal mortality (Pathway C), resulting in a positively selected, more resilient cohort that survives the prenatal exposure and exhibits better outcomes later in infancy (Pathway D). Recent research has found evidence supporting increased pregnancy losses and birth declines under heat conditions (Conte Keivabu et al. 2024; Davenport et al. 2020; Hajdu & Hajdu 2023). Whether these pregnancy losses are selective, disproportionately affecting weaker conceptions while stronger ones survive to birth, has barely been investigated. Some evidence suggests that prenatal exposure to high temperatures may lead to better educational and literacy outcomes during childhood (Wilde et al. 2017). If this pathway is more dominant, we would expect prenatal heat stress to lead to an increase in pregnancy loss and a decrease in infant mortality. We hypothesize:

H2a: Prenatal heat exposure is positively associated with pregnancy loss.

H2b: Prenatal heat exposure is negatively associated with infant mortality.

2.2 Behavioural mediators: Prenatal and postnatal behaviours

In addition to the physiological pathways, behavioural adaptations by pregnant women and their families could function as mediators in the relationship between prenatal heat stress and infant mortality. Two key behavioural factors that may play a role in the relationship between prenatal heat exposure and infant mortality are prenatal maternal health behaviour and postnatal parental investment.

It is well-established that prenatal maternal behaviours such as the antenatal care a mother receives during a pregnancy, are essential for preventing pregnancy complications and promoting infant wellbeing (Carroli, Rooney, et al. 2001; Carroli, Villar, et al. 2001; Waldenström & Turnbull 1998) (Pathway E). Research has shown that environmental factors during pregnancy can lead to behavioural adaptations aimed at reducing pregnancy risks. For instance, exposure to local violence has been associated with increases in antenatal care visits as a means to mitigate pregnancy risks, which in turn improved birth outcomes (Torche & Villarreal 2014). In contrast, high temperatures are more likely to disrupt health-seeking behaviour by limiting mobility (Samano et al. 2021). Specifically, pregnant women may reduce outdoor activities to protect themselves from heat exposure which can hinder access to care and consequently exacerbate pregnancy-related risks (Pathway F). Heat could also affect healthcare infrastructure and quality of care (Kjellstrom et al. 2016), further diminishing access to prenatal care. A decrease in prenatal care can result in missed opportunities for promoting healthy pregnancy development, potentially leading to negative consequences for both health at birth (Pathway G) and in-utero mortality (Pathway H). We hypothesize:

H3a: Prenatal heat exposure is negatively associated with the number of antenatal care visits.

H3b: The relationship between prenatal heat exposure and infant mortality is mediated by antenatal care visits.

In addition, compensatory parental behaviours after birth could also mediate the relationship between heat exposure and infant mortality. Heat exposure during gestation may prompt parents to invest differently in the development of their children after birth (Pathway I) if the child is less-endowed precisely because of prenatal heat exposure (Pathway J). On the one hand, parents could address the impact of heat-induced disadvantages at birth with compensatory behaviours that aim to improve the infant's health and development (Del Bono et al. 2012; Pitt et al. 1989). Conversely, under a reinforcement mechanism, families may engage in behaviours that exacerbate early-life disadvantages in infancy (Behrman & Rosenzweig 2004; Datar et al. 2010; Rosenzweig & Schultz 1982). In our study, reinforcement of disadvantages at birth would (further) increase infant mortality, whereas the compensation of disadvantages at birth would decrease (or at least not increase) infant mortality.

Socioeconomic characteristics tend to influence parents' decision to redistribute resources in ways that either compensate for or reinforce early-life disadvantages. Maternal education plays a key role in this redistribution decision (Lin et al. 2007; Prickett & Augustine 2016; Restrepo 2016). Reinforcing effects are found to be "minimal among less-educated mothers, [while] compensatory effects [are particularly significant] among the most-educated mothers" (Hsin 2012:13). If parents engage in compensatory or reinforcing behaviours after birth, maternal education could moderate the relationship between health at birth and infant mortality. As this pathway only operates if prenatal heat exposure reduces health at birth, we need to first establish that prenatal heat exposure reduces health at birth and then hypothesize that maternal education buffers the adverse effect of prenatal heat exposure on infant survival:

H4a: Prenatal heat exposure is negatively associated with health at birth.

H4b: The positive impact of prenatal heat exposure on infant mortality is weaker—and may be null or even negative—among children of more-educated mothers compared to those of less-educated mothers.

2.3 Other mechanisms

If prenatal heat exposure reduces infant mortality, another mechanism that could be considered to explain these reductions relates to protective conditions of the mother in late pregnancy. Pregnant mothers might stay indoors, reduce their workload, and receive familial and other care when it is very hot or migrate to their parental home for birth, with beneficial consequences for their pregnancy health and the health of their newborn. So far, no direct empirical evidence exists on a shift of exposure patterns indoors in Mali during heat episodes.

Nor is there empirical evidence on whether migration patterns to the parental home are systematically associated with heat exposure. Some studies provide related insight. On the one hand, a global study shows that extreme heat reduces individuals' income because of reduced working hours in regions with a larger share of agricultural workers (Kroeger 2023). Additionally, globally the agricultural sector accounts for about two-thirds of heat-related labor hour losses (Romanello 2022). On the other hand, mothers may not reduce their workload under episodes of extreme heat, at least not their domestic workload as a qualitative study in Kenya shows (Scorgie 2023). Hence, from existing literature it is unclear whether maternal indoor exposure patterns in Mali could differ because of locational changes that are systematically related to gestational heat exposure. The DHS also does not include information on locational changes during pregnancy.

Three arguments can be made against increased maternal indoor exposure driving heat-induced infant mortality. First, even if mothers are indoors, they are likely still exposed to extreme levels of heat and unable to effectively shield themselves from harmful exposure due to a lack of availability of cooling technologies. The ownership rate of cooling devices is less than 5 % of households and the air-conditioning (AC) ownership rate is .08 units per household in Africa (International Energy Agency 2022). Even projections of AC penetration by 2050 yield that penetration in southern and western Africa would remain below 5 % and be limited to main urban areas (Falchetta and Mistry 2021).

Second, it is important to keep in mind that the temperature data we use (gridded, high-resolution hourly measurements from ERA5-Land) are based on temperature in the shade. This means that the temperature values that are captured in our exposure measurements actually reflect shaded conditions, rather than outdoor conditions under the sun. They hence serve as a conservative lower bound that does not incorporate the effect of solar radiation.

Third, the mechanisms could be conceptualized as an exposure classification issue, where it could be argued that migrating mothers would induce exposure misclassification, which should usually result in estimate bias towards the null. Exposure misclassification bias could arise if heat conditions measured at the mother's location at the time of the interview are attributed to a pregnancy during which she did not reside at that location—such as if she only visited the area or migrated there during or after the pregnancy. It is still possible that some women may have migrated to their natal home to give birth and then returned to their primary residence afterward. This is common in the case of Fulani women, who may return to their parents' home to give birth and stay there for several years while their husbands work elsewhere (Castle, 1995). Although they may stay away for several years, our sample includes children born within five years prior to the survey—making it unlikely that this migration pattern would apply to most of the mothers in our sample. For robustness, we conduct a supplementary analysis (not shown here) in which we restrict the sample to children whose mothers are not Fulani and find that results are robust. We exclude children whose mother was not residing in the PSU in the year before their birth from all analysis.

Furthermore, this mechanism would be difficult to test with the DHS and lead to inconclusive results. An indirect test of this mechanism would be to see if heat-induced infant mortality reductions are larger for mothers in agricultural occupations because heat risks are disproportionate for them and they might hence be most likely to reduce their working hours during heat episodes. While DHS provides information on occupational types, the results of this test would not be unambiguously interpretable. If the effect of extreme heat functions through a prenatal mortality mechanism instead, we would expect to see larger reductions for agricultural workers, too, as they are directly exposed to extreme heat outdoors without shielding and under physical strain. This means that the two opposing hypotheses would be associated with the same heterogeneity pattern. For this reason, we would be unable to disentangle the two mechanisms with this empirical test. Therefore, we provide no empirical tests of this mechanism.

2.4 Population and climate in Mali

Mali provides an ideal setting for examining the impact of heat exposure on infant mortality for two key reasons. Firstly, the country continues to experience high infant mortality rates—65.7 deaths per 1,000 live births in 2018 (UNICEF 2024), which enables an analysis of how environmental factors correlate with infant mortality.

Secondly, in many Sub-Saharan African climates, it is difficult to separate the effects of heat stress, disease, and food insecurity on infant mortality, as these factors often overlap. High temperatures can harm birth outcomes and infant health (Andriano 2023; McElroy et al. 2022), while the wet season increases the risks of both malaria infection and food insecurity (Duque et al. 2022), which also threaten maternal and infant wellbeing. However, Mali presents a unique case because its hot and wet seasons do not overlap. This seasonal separation allows us to isolate the impact of extreme heat during the hot, dry season without interference from the effects of malnutrition and infectious disease (Grace et al. 2021), which are more prevalent during the wet season. Heat exposure measurements in Mali are therefore less likely to be correlated with food insecurity and disease, making it easier to identify heat stress as a distinct environmental driver of infant mortality.

The climate of Mali is characterized by three distinct seasons. During the dry season between March and June, maximum temperatures range between 36.7°C and 41.1°C, and precipitation is less than 40 mm per month. The dry season is followed by the rainy season from June to September, during which monthly precipitation can reach up to 110.2 mm. Finally, during the cold season from October to February, minimum temperatures can be as low as 14.3°C in January, while maximum temperatures remain above 29°C on average. Since 2000 mean temperatures have consistently exceeded 29°C indicating a sustained warming trend compared to previous decades. (World Bank Climate Change Knowledge Portal 2021)

3 Data and Variables

3.1 Data

Our analytical approach combines two data sources: 1) micro-level data from the 2018 Mali Demographic and Health Survey (MDHS) (INSTAT et al. 2019), which provides information on female respondents in reproductive ages (15–49) and their children born in the period 2014–2018; and 2) the gridded temperature data from the ERA5-Land dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service, 2019).

The 2018 MDHS provides two pieces of information that are crucial for linking heat conditions with health outcomes. Firstly, it provides the GPS coordinates of the community where women and their children live (i.e. primary sampling unit, PSU), which allows us to measure the heat conditions children were exposed to during gestation. Secondly, this survey provides information on children's date of birth and gestational lengths which helps construct trimesters of gestation while accounting for varying gestational lengths. This is particularly useful in a country where preterm birth rates are estimated to range from 10 to 37.4% (Blencowe *et al.* 2012; Cao et al., 2022).[25]

The ERA5-Land from the ECMWF reanalysis provides complete and consistent hourly measurements of land variables from 1950 on a global grid at a fine resolution of 0.1×0.1 degrees (around 9 km at the equator) (Muñoz Sabater et al. 2019). As a reanalysis product, ERA5-Land values are based on simulation as well as observations from a wide range of data sources, such as weather stations, satellites, radars, radiosondes. ECMWF data has been used in environmental demographic research due to its consistency and because it overcomes scarce station availability in our area of study (Hersbach et al. 2020; Zandler et al. 2020).

We use hourly data on maximum temperatures to calculate the daily maximum temperature for all grid cells in Mali between 5 November 2012 and 28 October 2018[26]. To account for the random displacement of the GPS coordinates undertaken by the DHS to preserve respondents' anonymity, we create a 10-km buffer zone around each PSU and

[25] In the absence of this information, a commonly used approach to construct prenatal exposure measures is to assume a standard 40-week or 9-month pregnancy duration.

[26] These days represent respectively the earliest day of conception and the latest day of birth in our sample.

calculate the weighted average daily temperature for this area, using the proportion of each intersecting temperature grid cell that falls within the buffer as weights. We use the same approach to construct rainfall controls. We leverage information on women's migration histories to exclude from the analytic sample all children whose mother was not residing in the PSU in the year before their birth (510 children) and thus ensure an accurate measurement of exposure to heat conditions during gestation.[27] The final sample includes 9,016 children.[28]

3.2 Variables

Infant mortality (main outcome): The main outcome variable is an indicator variable for death before the first birthday.

Prenatal heat exposure (treatment): To identify effects of prenatal heat exposure on infant mortality, we use three distinct treatment variables for each trimester of pregnancy. The treatment variables capture the number of days in each trimester of pregnancy where the daily maximum temperature falls between 95°F and 100°F, 100°F and 105°F, and above 105°F (or in degrees Celsius, 35°C, 37.8°C, 40.6°C). These thresholds capture levels of extreme heat that are relevant to body thermoregulation and allow us to provide estimates for different heat intensities.

We use children's date of birth and gestational length at birth to define the timing of each trimester of pregnancy. The conception date is first estimated by subtracting the gestational length at birth (given in completed months and converted to days by multiplying each month by 28) from the date of birth. The first trimester of pregnancy is then defined as the first 12 weeks since conception, followed by an additional 14 weeks

[27] By excluding children whose mother was not residing in the PSU in the year before their birth, we eliminate exposure misclassification bias. Exposure misclassification bias could arise if heat conditions measured at the mother's location at the time of the interview are attributed to a pregnancy during which she did not reside at that location—such as if she only visited the area or migrated there during or after the pregnancy. Usually, exposure misclassification results in estimate bias towards the null.

[28] While our analytic sample includes multiple births, we present results excluding them and find that results are substantively consistent (Appendix Table 4 Model E).

for the second trimester of pregnancy, and with the remainder of the pregnancy days assigned to the third trimester.

Two reasons motivate our choice to use temperature bins across the three pregnancy trimesters to measure prenatal heat exposure. Firstly, using temperature bins allows us to capture the effects of varying thresholds of heat intensity, whereas other studies only use one threshold or the monthly mean/maximum temperature (Grace et al. 2021; Wilde et al. 2017). Our approach is particularly useful to capture non-linearities in the relationship between heat intensity and the outcome of interest (Barreca et al. 2018; Dell et al. 2014). Secondly, analyzing heat effects in each trimester of gestation rather than a broader pregnancy exposure (Gray & Thiede 2024; Thiede et al. 2022) provides insight into the most sensitive period of pregnancy.

Controls: We add a set of individual, parental, and community control variables. The individual controls include the child's birth order (categorized as 1, 2, 3, 4, and 5+) and sex. Parental variables control for maternal age at birth (categorized as under 16 years, 17–19, 20–24, 25–29, 30–34, and 35+ years), maternal educational attainment (categorized as 'no formal education', 'primary education', and 'secondary and higher education'), the education level of the mother's most recent partner (categorized as 'no formal education', 'primary education', 'secondary and higher education', and 'don't know/ missing'; the 'don't know/missing' category implicitly controls for marital status as this question is only asked to women who are in a union at the time of the interview). Community controls include the place of residence ('urban' or 'rural') and the average amount of rainfall during each trimester of gestation.

3.3 Empirical Strategy

To estimate the effect of in-utero heat exposure on infant mortality, we employ a linear probability model with region-by-month-of-birth and region-by-year-of-birth fixed effects. The model reads as follows:

$$death_{icrdmy} = ¿ \quad \beta_0 + \tag{1}$$

$$\sum_{j=1}^{3} \beta_j^1 heat_{j,cdmy}^1 + \sum_{j=1}^{3} \beta_j^2 heat_{j,cdmy}^2 + \sum_{j=1}^{3} \beta_j^3 heat_{j,cdmy}^3 + \sum_{t=1}^{3} \gamma_t rain_{cdmy}^t .$$

The outcome $death_{icrdmy}$ indicates the death of infant *i* born in cluster *c* in region *r* on day *d* of month *m* of year *y*, before reaching its first birthday. For each of the child's three gestational trimesters, $heat_{j,cdmy}^{1-3}$ captures the number of days across three heat bins *j*: 1 = 95–100°F, 2 = 100–105°F, 3 = over 105°F. $\sum_{t=1}^{3} \gamma_t rain_{cdmy}^t$ account for the average amount of rainfall in each trimester of gestation, and $x_i^{'}$ controls for child, parental and community characteristics. We adopted a fixed effects approach widely employed in the literature which exploits the quasi-random fluctuations of heat exposure that occur within regions (i.e. first administrative level)[29] and calendar month (Andriano 2023; Conte Keivabu 2022; Wilde et al. 2017). The region-by-month-of-birth fixed effect α_{rm} controls for seasonal trends in regional factors that affect the heat exposure or infant mortality. The region-by-year-of-birth fixed effect δ_{ry} controls for annual shocks and changes in heat exposure that are correlated over time with changes in infant mortality at the regional level (Barreca et al. 2018). Standard errors are clustered by region.

In supplementary analyses, we use three alternative measures of heat exposure (see Appendix Table 1 for results). Firstly, recognizing that heat exposure can increase premature birth (Andriano 2023) which may reduce exposure duration, we adjust our treatment variables by dividing them by the total number of days in gestation (see Appendix Table 1 Model C)[30]. Secondly, we create relative measures of heat exposure

[29] In Mali, there are 10 regions and the capital district Bamako. The 2018 MDHS covers the population in Bamako and eight of the 10 regions (Gao, Kayes, Kidal, Koulikoro, Mopti, Segou, Sikasso, Timbuktu) because population density is very low in Ménaka and Taoudénit.

[30] While 96.0% of the babies in our sample were born at nine months of gestation, 3.9% were born at seven, eight or ten months of gestation (see Appendix Table 2). A baby born full-term could be

that account for differences in climate adaptation. These measures count the number of days in each trimester of gestation where the daily maximum temperature falls into the 90–95th, 95–99th, and above the 99th percentile of the cluster's daily maximum temperature distribution over a 15-year period (see Appendix Table 1 Model B). Thirdly, we adjust these relative threshold-based measures of heat exposure by gestational length (see Appendix Table 1 Model D). Finally, we also model the heat-mortality relationship using a logistic regression model (see Appendix Table 3). These analyses yield consistent results.

4 Results

4.1 Descriptive statistics

Table 1 shows descriptive statistics for the variables used in the analysis. Of the 9,016 children in our sample [31], 4.9% (446) died before completing their first year of life. Males account for 50.8% (4,584) of the children. The majority of children live in a rural area (76.1%), and most mothers and their partners have received no formal education (73.4% and 71.0%). On average, in a trimester there are between 13.3 and 15.8 days where the daily maximum temperature is between 95–100°F, between 14.5 and 19.4 days with a maximum temperature of 100–105°F, and between 7.6 and 10.1 days with a maximum temperature above 105°F.

Table 1: Descriptive Statistics

Variable	**Frequency (percentage)/ Mean (standard deviation)**
Outcome	
Infant death (age at death <12 months)	

exposed to up to a maximum of 14 weeks of heat in the third trimester of gestation, whereas a baby born 4 weeks prematurely could only be exposed to up to 10 weeks of heat for the third trimester of gestation. To address these differences in exposure duration, we divide our treatment variables by the total number of days in gestation.

[31] In our sample there are seven children whose birth occurred during the second trimester of gestation. Because they have no heat exposure during the third trimester of gestation, they are excluded from the regression. (See Appendix Table 2 for a detailed overview of the distribution of gestational length at birth in our sample.)

Alive at first birthday (total)	8,577 (95.06%)
(among female)	4,241 (95.54%)
(among male)	4,336 (94.59%)
Dead at first birthday (total)	446 (4.94%)
(among female)	198 (4.46%)
(among male)	248 (5.41%)
Heat exposure variables	
Number of heat days in each trimester (absolute thresholds)	
95–100°F day – first trimester	15.84 (11.04)
95–100°F day – second trimester	19.06 (11.53)
95–100°F day – third trimester	13.34 (9.78)
100–105°F day – first trimester	14.61 (15.84)
100–105°F day – second trimester	19.39 (18.61)
100–105°F day – third trimester	14.54 (15.16)
>105°F day – first trimester	8.01 (15.14)
>105°F day – second trimester	10.06 (16.62)
>105°F day – third trimester	7.64 (13.34)
Controls	
Infant sex	
Female	4,439 (49.20%)
Male	4,584 (50.80%)
Birth order	
1	1,508 (16.71%)
2	1,558 (17.27%)
3	1,432 (15.87%)
4	1,230 (13.63%)
5+	3,295 (36.52%)
Maternal age at birth	
12–16 years	420 (4.65%)
17–19	1,080 (11.97%)
20–24	2,346 (26.00%)
25–29	2,169 (24.04%)
30–34 years	1,652 (18.31%)
35+ years	1,356 (15.03%)
Maternal education	
No education	6,623 (73.40%)
Primary education	1,087 (12.05%)
Secondary and higher education	1,313 (14.55%)
Mother's partner's education	
No education	6,409 (71.03%)
Primary education	782 (8.67%)
Secondary and higher education	1,534 (17.00%)
Missing (mother unmarried or not in union)	298 (3.30%)
Urban/rural	
Rural	6869 (76.13%)
Urban	2154 (23.87%)

Mothers	5,844
DHS clusters	328
N (children)	9,016

Source: Authors’ calculations based on Mali DHS 2018

*Note: Sample based on children from the Mali DHS 2018 Children’s Recode File, recording live births of the respondent in the five years prior to the interview. Women who were not resident at the DHS cluster location in the year prior to birth (based on their age at move) were excluded from the sample (see section **3. Data**). Absolute thresholds in degrees Fahrenheit correspond to 35–37.78°C, 37.78–40.56°C, >40.56°C in degrees Celsius.*

4.2 Gestational heat impacts on infant mortality

In this section, we present the results of the regression model analyzing the effect of prenatal heat exposure on infant mortality. As our independent variables for each trimester represent the number of days where the daily maximum temperature falls into one of the three temperature bins (95–100°F, 100–105°F, and over 105°F), the estimates indicate the effect of one additional hot day in the trimester relative to a day with maximum temperature below 95°F. We multiply the estimates by 100 to express the effects as percentage point changes.

Figure 2 shows the impact of heat exposure on infant mortality across trimesters of gestation (see Model A in Appendix Table 1 for estimates and standard errors[32]). For the first trimester, we find no significant association between heat exposure and infant mortality. However, heat exposure during the second and third trimesters of gestation is negatively associated with infant mortality. In the second trimester of gestation, each additional day between 100 and 105°F decreases the probability of infant mortality by 0.06 percentage points (p-value < 0.05) and each additional day over 105°F decreases the probability of infant mortality by 0.11 percentage points ($p < .01$). In the third trimester of gestation, infant mortality is reduced by 0.16 percentage points for each additional day between 95 and 100°F ($p < .05$), by 0.13 percentage points for each additional day between 100 and 105°F ($p < .05$), and by 0.15 percentage points for each additional day

[32] The tables report the estimates and standard errors of the main independent variables. Full results are available upon request.

over 105°F ($p < .05$). These are substantively large coefficients if we consider the high numbers of hot days babies are exposed to during gestation in our sample. For example, babies in our sample are exposed to on average 19 days between 100 and 105°F, 10 days over 105°F during the second trimester, and between 8 and 15 hot days during the third trimester of gestation. The estimated coefficients are also large considering that in our sample there is a 1.8 percentage point difference in the average risk of infant death between mothers with no/primary education (5.2%) and mothers with secondary/higher education (3.4%). To summarize, the negative effect of heat exposure on infant mortality confirms hypothesis H2b.

Figure 2: Estimates for the effect of prenatal heat exposure in each gestational trimester on infant mortality

Fig. 2: Percentage point change in the probability of infant mortality for one additional heat day in each gestational trimester with 95% confidence intervals from a linear probability model. Outcome defined as the infant's death before reaching its first birthday. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; N = 9,016, Adj. R2: 0.016, Within R2: 0.011.

4.3 Physiological mechanism: *In utero* mortality

We find that prenatal heat exposure is associated with lower infant mortality. As posited in our conceptual framework, one mechanism that may explain why prenatal heat exposure reduces mortality is selective culling. Prenatal heat exposure may lead to intensified in-utero mortality that disproportionately affects weaker fetuses, leading to the selection of a cohort of stronger newborns that have better chances of surviving to their first birthday. In the following, we therefore test this selection hypothesis by investigating the impact of heat exposure on pregnancy terminations.

Using a question available in the DHS asking women whether they "ever had a pregnancy that terminated in a miscarriage, abortion or stillbirth, i.e. did not result in a live birth" (ICF 2018:51), we construct a new binary dependent variable indicating that the pregnancy was terminated. This variable includes both pregnancy losses and induced abortions. In supplementary analyses, we conduct further analyses to conclude that the broad definition of pregnancy terminations in our data should not affect our findings. For further details on the pregnancy termination data and analysis, see supplementary information on Figure 3 in the Appendix. Since the 2018 MDHS has information on *only the last* known pregnancy termination, we restrict this analysis to the respondent's last pregnancy (which can be either a pregnancy termination or a live birth). The treatment variables are constructed by dividing the number of hot days during pregnancy by the total number of gestational days to adjust for varying gestational length. We predict the probability of pregnancy termination by estimating the same model as in Eq. (1), where the treatment variables capture heat exposure throughout the entire pregnancy period for each heat bin.[33]

[33] Our analytic sample, which is restricted to the respondent's last pregnancy, includes 5,708 live births (97.7%) and 132 non-live births (2.3%). Since more than 70% of the pregnancy terminations occur during the second trimester (see Appendix Table 5), we collapse the exposure variables for the three trimesters of pregnancy into one exposure variable for the entire pregnancy. Specifically, the treatment variables capture the number of hot days during the entire gestational period for each of the three heat bins. See supplementary information for more information on the analytic sample used for this analysis.

Figure 3 presents the results of the impact of gestational heat exposure on pregnancy termination (see Appendix Table 4 for estimates and standard errors). We find that heat exposure during pregnancy is associated with an increased probability of pregnancy termination. Specifically, we find that a 1-SD increase in the proportion of days between 100–105°F during pregnancy increases the probability of pregnancy termination by 6.3 percentage points (SD = 0.10, $p < .01$). Similarly, a 1-SD increase in the proportion of days over 105°F increases the probability of pregnancy termination by 3.9 percentage points (SD = 0.11, $p < .05$). Given an average pregnancy termination of 2.3%, the magnitude of these estimates is fairly large. This finding aligns with the hypothesis that maternal heat exposure during pregnancy is associated with an increased risk of pregnancy termination (H2a). The finding that heat exposure above 100°F both increases the probability of pregnancy termination and reduces the probability of infant mortality aligns with our hypothesis that prenatal heat exposure leads to an increase in in-utero mortality that selects out weaker fetuses and leads to a stronger cohort of births with lower infant mortality.

Figure 3: Effects of heat exposure during pregnancy on the probability of the last pregnancy ending in termination

Fig. 3: Percentage point change in the probability of the pregnancy ending in termination for one additional heat day in gestation with 95% confidence intervals from a linear probability

model. Outcome defined as the pregnancy ending in a termination (miscarriage, stillbirth, abortion). Heat exposure variables measure the number of days in the gestation where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; N = 9,016, Adj. $R2$: 0.089, Within $R2$: 0.065.

4.4 Behavioural mechanisms: Antenatal care and postnatal investment

Behavioural adaptations by pregnant women and their family might be mediating the effects of prenatal heat stress on infant mortality. To investigate whether a behavioural response to extreme heat could explain the effect of extreme heat on in-utero mortality and the following decrease in infant mortality, we first explore whether heat exposure negatively impacts antenatal care visits. Antenatal care is critical for preventing pregnancy complications and ensuring the wellbeing of infants (Carroli, Rooney, et al. 2001; Carroli, Villar, et al. 2001; Waldenström & Turnbull 1998). Using a negative binomial regression model which controls for overdispersion, we test whether exposure to extreme heat during pregnancy leads to fewer antenatal care visits.

The results, displayed in Figure 4 (see Appendix Table 6 for estimates and standard errors), suggest that heat exposure during pregnancy is negatively associated with the number of antenatal care visits. We find that each additional day between 100 and 105°F during the pregnancy decreases the number of antenatal visits by 0.2% ($p < .05$). The estimates for the effect of each additional day between 95 and 100°F and over 105°F are also negative and of similar magnitude but not statistically significant ($p < .1$, and $p > .1$).

Figure 4: Estimates for the effect of gestational heat exposure on the number of antenatal care visits for the pregnancy

Fig. 4: Percentage change in the number of antenatal care visits for the pregnancy for one additional heat day in gestation with 95% confidence intervals from a negative binomial model. Outcome defined as the number of antenatal care visits. Heat exposure variables measure the number of days in the gestation where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 5,559, Null deviance: 9579.1 on 5726 df, Residual deviance: 7928.6 on 5558 df, AIC: 24199, 2 x log-likelihood: -23859.228.

Next, we conduct a mediation analysis to test whether the impact of prenatal heat exposure on infant mortality is mediated by the number of antenatal care visits. We restrict the analysis to children with information on antenatal care and use the same model specification as in our main result (Eq. 1) with and without the antenatal care variable. We find no evidence that antenatal care visits are associated with infant mortality nor that the effect of prenatal heat exposure on infant mortality is decreased when the antenatal care variable is included in the regression model (see Models A, B, and C in Table 2). This suggests that while heat exposure may impact the number of antenatal care visits a mother receives for a pregnancy, in line with hypothesis H3a, this behavioural mechanism does not mediate the negative relationship between prenatal heat exposure and infant mortality as hypothesized in H3b.

Table 2: Results from linear probability models for a mediation analysis for the effect of prenatal heat exposure on infant mortality with the mediator antenatal care visits

Heat exposure	Trimester	β	Percentage point change	SE
Model A. Prenatal heat exposure effects on infant death probability				
95–100°F day	(1)	0.0005	0.054	0.0002
95–100°F day	(2)	-0.0004	0.038	0.0004
95–100°F day	(3)	-0.0007	0.074	0.0005
100–105°F day	(1)	0.0007	0.071	0.0004
100–105°F day	(2)	-0.0003	0.027	0.0004
100–105°F day	(3)	-0.0010	0.095	0.0005
>105°F day	(1)	0.0006	0.058	0.0010
>105°F day	(2)	-0.0005	0.045	0.0003
>105°F day	(3)	**-0.0013***	**0.135**	**0.0005**
Model B. Association of the number of antenatal care visits and infant mortality				
Number of antenatal care visits	/	0.0001	0.006	0.0017
Model C. Prenatal heat exposure effects on infant death probability with mediator (number of antenatal care visits)				
95–100°F day	(1)	0.0005	0.054	0.0002
95–100°F day	(2)	-0.0004	0.038	0.0004
95–100°F day	(3)	-0.0007	0.074	0.0005
100–105°F day	(1)	0.0007	0.071	0.0004
100–105°F day	(2)	-0.0003	0.027	0.0004
100–105°F day	(3)	-0.0010	0.095	0.0005
>105°F day	(1)	0.0006	0.058	0.0010
>105°F day	(2)	-0.0005	0.045	0.0003
>105°F day	(3)	**-0.0013***	**0.135**	**0.0005**
Number of antenatal care visits	/	0.0001	0.002	0.0017

Notes: Results for a linear probability model estimating prenatal heat impacts on infant mortality. Percentage point change in infant death probability for one additional heat day in each gestational trimester with 95% confidence intervals. Model A. shows the impact of prenatal heat exposure on infant mortality for the subsample where antenatal care information is available. Model B. shows the association between antenatal care visits and infant mortality. Model C. shows the same model as Model A. with addition of the mediator variable of antenatal care visits. Outcome defined as infant's death before reaching its first birthday. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Antenatal care mediator defined as the number of antenatal care visits (categories: 1, 2, 3, 4, 5, 6, 7, 8, 9+). Models estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects. Controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth (12–20; 21–34; 35+ years), maternal education (no; primary; secondary/higher education), the mother's most recent husband's or partner's education (no; primary; secondary/higher education), urban/rural status of the cluster, birth order (1; 2; 3; 4; 5+), and infant sex. For further information on data and modelling, please refer to section 3–5.

N = 5,727
Sources: Mali DHS 2018, ERA5-Land
†p < .10; *p < .05; **p < .01

We next move to examining whether compensatory parental behaviours after birth mediate the relationship between prenatal heat exposure and infant mortality. As this pathway only operates if prenatal heat exposure reduces health at birth, we need to first establish that prenatal heat exposure reduces health at birth. We estimate a new model where our dependent variable is size at birth, an ordinal measure with five levels (very small, smaller than average, average, larger than average, and very large) which we treat as continuous in our analysis.[34] Results, depicted in Figure 5 (see Appendix Table 7 for estimates and standard errors), reveal that heat exposure (95–100°F) during the third trimester of gestation *increases* size at birth. We find no significant effects of heat exposure during the first and second trimesters of gestation on size at birth. As we find no evidence that prenatal heat exposure decreases size at birth (counter to hypothesis H4a), it follows that differential investments by maternal education (H4b) are unlikely to occur, as such investments would only arise in response to a decrease in size at birth caused by heat exposure.

Figure 5: Estimates for the effects of prenatal heat exposure in each gestational trimester on infant size at birth

[34] While most studies use birthweight as a proxy for health at birth, this variable is missing for 64.2% of our sample. By contrast, size at birth is available for all children and has been shown to be a reliable proxy for birthweight (Walton et al. 2000). We also estimate the model on the subsample with available birthweight data and find consistent results: heat exposure during the third trimester of gestation is associated with higher birthweight and a lower probability of low birthweight (Appendix Table 8).

Fig. 5: Percentage point change in the infant's size at birth for one additional heat day in each gestational trimester with 95% confidence intervals from a linear probability model. Outcome defined as the infant's size at birth based on maternal perception with categories: 1) very small, 2) smaller than average, 3) average, 4) larger than average, 5) very large. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; N = 9,016, Adj. R2: 0.030, Within R2: 0.009.

5 Discussion and conclusion

In light of the rapid and prolonged temperature increases in recent years and projections for future years, extreme heat poses an important risk to populations in low- and middle-income countries (IPCC 2023). The effects of prenatal exposure to extreme heat for mortality outcomes are still not well understood. So far, the literature has primarily focused on the role of prenatal environmental factors such as malnutrition and vector-borne disease in influencing mortality, rather than on the distinct effect of extreme heat (Kudamatsu et al. 2012; Kumar et al. 2016; Rocha & Soares 2015). Our paper has provided a conceptual overview of how prenatal exposure to extreme heat might impact infant mortality and applied theoretical expectations to the case of Mali. Specifically, we analyzed data from 9,016 live births from the 2018 Mali Demographic and Health Survey to explore the impact of prenatal exposure to extreme heat on infant mortality and investigate physiological and behavioural mechanisms that may drive these effects.

We found that prenatal heat exposure during gestation decreases the risk of infant mortality. Specifically, we found that heat exposure during the second and third trimesters of gestation significantly reduces infant mortality. While the reductions in infant mortality may appear beneficial in isolation, our finding cannot be interpreted as an improvement of population health under extreme heat. Indeed, we found that heat exposure during gestation increases the probability of pregnancy termination, suggesting that the effect of heat exposure on infant mortality may at least partly be driven by fetal loss which selects out the weaker fetuses and leads to a stronger cohort of births with lower infant mortality. These findings point to the importance of the direct link between prenatal heat exposure and selective culling (Pathway C in our conceptual framework), complementing previous findings that climate extremes may be a substantial risk factor for reproductive health (Davenport et al. 2020) and consequently contribute to maternal morbidity and mortality (Farren et al. 2016; Quenby et al. 2021).

Guided by our conceptual framework, we also examined whether maternal behavioural responses could mediate the relationship between prenatal heat exposure and infant mortality. Firstly, we showed that extreme heat during pregnancy decreases the number of antenatal care visits suggesting that environmental shocks during pregnancy could disrupt healthcare access and utilization. However, we found no evidence that this reduction in antenatal care visits mediates the relationship between prenatal heat exposure and infant mortality. Secondly, our findings indicate that prenatal heat exposure does not reduce size at birth but rather increases it during the third trimester of gestation. This challenges our initial expectations that differential maternal investments that would arise in response to a reduction in size at birth could mediate the relationship between prenatal heat exposure and infant mortality. Our finding that heat exposure during the third trimester of gestation improves health at birth runs contrary to existing literature (Andriano 2023; Grace et al. 2021). This discrepancy may be due to variations in the measurement of heat exposure and the outcome, or the sample used in these studies. For example, Grace et al. (2021) focus on the impact of heat exposure above 100°F on birthweight and include the Mali 2000, 2006, and 2012 DHSs in their sample, where gestational length information is not available. Our finding that prenatal heat exposure increases size at birth further supports the hypothesis of in-utero selection, where prenatal heat exposure leads to the loss of more vulnerable pregnancies, leaving behind stronger ones that have higher size at birth. However, the lack of evidence for these mediators in our setting does not rule out the possibility that behavioural factors might mediate the relationship between other climate extremes and infant mortality, which should be considered in future studies.

Our finding that prenatal heat exposure reduces infant mortality suggests that selective culling outweighs the scarring effects induced by prenatal heat exposure. Previous studies identified that extreme heat increases the risk of non-live birth (Davenport et al. 2020; Hajdu & Hajdu 2023). We provide further evidence that such culling effects may disproportionately affect weaker offspring and lead to selection, in line with Wilde et al. (2017) who find that prenatally exposed children have improved educational attainment. Our study thus demonstrates that prenatal insults can have counterintuitive consequences for population health outcomes because of intensified selection in the prenatal period (Bruckner & Catalano 2018; Nobles & Hamoudi 2019). Further, our findings also imply that isolating outcomes in adulthood, which have received more attention in the literature (Brink et al. 2024; Fishman et al. 2019; Isen et al. 2017), may mask such early life selection and initial health advantages that shape cohort health across the life-course.

This finding also contrasts with previous studies indicating that prenatal drought exposure increases infant mortality (Flatø & Kotsadam 2014; Kudamatsu et al. 2012; Rocha & Soares 2015) and under-five mortality (Andriano 2024). A possible explanation for this discrepancy is that the mechanisms triggered by different types of climate extremes may vary. For example, maternal malnutrition—often associated with droughts—might not lead to sufficiently high fetal loss rates to create new cohorts that are positively selected on health. By contrast, maternal heat stress may increase fetal loss rates, potentially altering cohort composition and skewing observed mortality risks. This distinction between environmental conditions underscores the importance of investigating the specific pathways through which different climate extremes affect early childhood mortality. While our conceptual framework focuses exclusively on the relationship between prenatal heat exposure and early childhood mortality, it can guide empirical studies on the impact of other climate extremes. We therefore call for further research into the biological and socio-behavioural mechanisms underlying climate-population relationships concerning how prenatal exposures to various climate extremes affect both fetal outcomes and the long-term health of surviving infants. Such research would be instrumental in clarifying how targeted interventions could mitigate the distinct risks posed by different climate extremes.

It is important to acknowledge that this study has several limitations. Firstly, birth dates and gestational lengths are self-reported by the mother and may therefore be affected by recall error (Colacce et al. 2020; Haider et al. 2021). While we cannot rule out the possibility that recall errors and heaping of birth dates and gestational lengths could have led to the misclassification of heat exposures, these measurement errors are unlikely to be systematically correlated with heat exposure during pregnancy. Secondly, the DHS question on pregnancy termination does not differentiate between induced and spontaneous abortions. Although we cannot be certain that all reported pregnancy terminations refer to spontaneous abortions, restrictive abortion policies in Mali may deter respondents from reporting induced abortions and we found no evidence that socioeconomic status is correlated with increased pregnancy termination reports, which could otherwise indicate differential access to induced abortion by income.

To conclude, our analysis provides a conceptual framework that can be used to guide analyses on the impact of prenatal environmental shocks on health and mortality throughout the life course in other contexts. Populations across different countries and communities exhibit distinct institutional, socioeconomic, and environmental conditions, which impacts their exposure to heat. The impact of prenatal heat exposure on infant mortality can therefore depend on factors such as the severity and duration of climate extremes, access to protective infrastructure such as air conditioning, and the demands of local labor markets. In agricultural communities, for instance, pregnant women often engage in outdoor work for extended periods, increasing their vulnerability to heat-related health risks (Bonell et al. 2022). Our analysis highlights the need for more context-specific work, as these relationships between heat and mortality and health may differ across contexts.

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Figures

Figure 1: Conceptual framework on pathways through which prenatal heat exposure may impact infant mortality

Scarring
(disadvantages at birth,
e.g. low birthweight)

J

Postnatal parental investment
(compensatory/reinforcing
response to disadvantages at
birth)

A

B

G

I

Prenatal heat exposure

F

Prenatal maternal
behaviours
(e.g. antenatal care visits)

E

Infant mortality

H

C

D

Selective culling
(*in utero* mortality)

Figure 2: Estimates for the effect of prenatal heat exposure in each gestational trimester on infant mortality

Fig. 2: Percentage point change in the probability of infant mortality for one additional heat day in each gestational trimester with 95% confidence intervals from a linear probability model. Outcome defined as the infant's death before reaching its first birthday. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 9,016, Adj. R2: 0.016, Within R2: 0.011.

[**Figure 3**: Effects of heat exposure during pregnancy on the probability of the last pregnancy ending in termination]

Fig. 3: Percentage point change in the probability of the pregnancy ending in termination for one additional heat day in gestation with 95% confidence intervals from a linear probability model. Outcome defined as the pregnancy ending in a termination (miscarriage, stillbirth, abortion). Heat exposure variables measure the number of days in the gestation where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 9,016, Adj. R2: 0.089, Within R2: 0.065.

[**Figure 4**: Estimates for the effect of gestational heat exposure on the number of antenatal care visits for the pregnancy]

Fig. 4: Percentage change in the number of antenatal care visits for the pregnancy for one additional heat day in gestation with 95% confidence intervals from a negative binomial model. Outcome defined as the number of antenatal care visits. Heat exposure variables measure the number of days in the gestation where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 5,559, Null deviance: 9579.1 on 5726 df, Residual deviance: 7928.6 on 5558 df, AIC: 24199, 2 x log-likelihood: -23859.228.

[**Figure 5**: Estimates for the effects of prenatal heat exposure in each gestational trimester on infant size at birth]

Fig. 5: Percentage point change in the infant's size at birth for one additional heat day in each gestational trimester with 95% confidence intervals from a linear probability model. Outcome defined as the infant's size at birth based on maternal perception with categories: 1) very small, 2) smaller than average, 3) average, 4) larger than average, 5) very large. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 9,016, Adj. R2: 0.030, Within R2: 0.009.

Tables

[**Table 1**: Descriptive Statistics]

Variable	**Frequency (percentage)/ Mean (standard deviation)**
Outcome	
Infant death (age at death <12 months)	
Alive at first birthday (total)	8,577 (95.06%)
(among female)	4,241 (95.54%)
(among male)	4,336 (94.59%)
Dead at first birthday (total)	446 (4.94%)
(among female)	198 (4.46%)
(among male)	248 (5.41%)
Heat exposure variables	
Number of heat days in each trimester (absolute thresholds)	
95–100°F day – first trimester	15.84 (11.04)
95–100°F day – second trimester	19.06 (11.53)
95–100°F day – third trimester	13.34 (9.78)
100–105°F day – first trimester	14.61 (15.84)
100–105°F day – second trimester	19.39 (18.61)
100–105°F day – third trimester	14.54 (15.16)
>105°F day – first trimester	8.01 (15.14)
>105°F day – second trimester	10.06 (16.62)
>105°F day – third trimester	7.64 (13.34)
Controls	
Infant sex	
Female	4,439 (49.20%)
Male	4,584 (50.80%)
Birth order	
1	1,508 (16.71%)
2	1,558 (17.27%)
3	1,432 (15.87%)
4	1,230 (13.63%)
5+	3,295 (36.52%)
Maternal age at birth	
12–16 years	420 (4.65%)
17–19	1,080 (11.97%)
20–24	2,346 (26.00%)
25–29	2,169 (24.04%)
30–34 years	1,652 (18.31%)
35+ years	1,356 (15.03%)
Maternal education	
No education	6,623 (73.40%)
Primary education	1,087 (12.05%)
Secondary and higher education	1,313 (14.55%)
Mother's partner's education	

No education	6,409 (71.03%)
Primary education	782 (8.67%)
Secondary and higher education	1,534 (17.00%)
Missing (mother unmarried or not in union)	298 (3.30%)
Urban/rural	
Rural	6869 (76.13%)
Urban	2154 (23.87%)
Mothers	5,844
DHS clusters	328
N (children)	9,016

Source: Authors' calculations based on Mali DHS 2018

Note: Sample based on children from the Mali DHS 2018 Children's Recode File, recording live births of the respondent in the five years prior to the interview. Women who were not resident at the DHS cluster location in the year prior to birth (based on their age at move) were excluded from the sample (see section ***3. Data****). Absolute thresholds in degrees Fahrenheit correspond to 35–37.78°C, 37.78–40.56°C, >40.56°C in degrees Celsius.*

[**Table 2**: Results from linear probability models for a mediation analysis for the effect of prenatal heat exposure on infant mortality with the mediator antenatal care visits]

Heat exposure	**Trimester**	β	**Percentage point change**	**SE**
Model A. Prenatal heat exposure effects on infant death probability				
95–100°F day	(1)	0.0005	0.054	0.0002
95–100°F day	(2)	-0.0004	0.038	0.0004
95–100°F day	(3)	-0.0007	0.074	0.0005
100–105°F day	(1)	0.0007	0.071	0.0004
100–105°F day	(2)	-0.0003	0.027	0.0004
100–105°F day	(3)	-0.0010	0.095	0.0005
>105°F day	(1)	0.0006	0.058	0.0010
>105°F day	(2)	-0.0005	0.045	0.0003
>105°F day	(3)	**-0.0013***	**0.135**	**0.0005**
Model B. Association of the number of antenatal care visits and infant mortality				
Number of antenatal care visits	/	0.0001	0.006	0.0017
Model C. Prenatal heat exposure effects on infant death probability with mediator (number of antenatal care visits)				
95–100°F day	(1)	0.0005	0.054	0.0002
95–100°F day	(2)	-0.0004	0.038	0.0004
95–100°F day	(3)	-0.0007	0.074	0.0005
100–105°F day	(1)	0.0007	0.071	0.0004
100–105°F day	(2)	-0.0003	0.027	0.0004
100–105°F day	(3)	-0.0010	0.095	0.0005
>105°F day	(1)	0.0006	0.058	0.0010
>105°F day	(2)	-0.0005	0.045	0.0003
>105°F day	(3)	**-0.0013***	**0.135**	**0.0005**
Number of antenatal care visits	/	0.0001	0.002	0.0017

Notes: Results for a linear probability model estimating prenatal heat impacts on infant mortality. Percentage point change in infant death probability for one additional heat day in each gestational trimester with 95% confidence intervals. Model A. shows the impact of prenatal heat exposure on infant mortality for the subsample where antenatal care information is available. Model B. shows the association between antenatal care visits and infant mortality. Model C. shows the same model as Model A. with addition of the mediator variable of antenatal care visits. Outcome defined as infant's death before reaching its first birthday. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Antenatal care mediator defined as the number of antenatal care visits (categories: 1, 2, 3, 4, 5, 6, 7, 8, 9+). Models estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects. Controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth (12–20; 21–34; 35+ years), maternal education (no; primary; secondary/higher education), the mother's most recent husband's or partner's education (no; primary; secondary/higher education), urban/rural status of the cluster, birth order (1; 2; 3; 4; 5+), and infant sex. For further information on data and modelling, please refer to section 3–5.

N = 5,727
Sources: Mali DHS 2018, ERA5-Land
†p < .10; *p < .05; **p < .01

Appendix

Appendix Table 1: Results from linear probability models estimating the effect of prenatal heat exposure in each trimester on the probability of infant death

Heat exposure	Trimester	β	Percentage point change (β *100)	SD of predictor	Change in deaths for a 1-SD increase in heat exposure	SE
Model A. Number of heat days in trimester with absolute thresholds						
95–100°F day	(1)	0.000	0.014	11.039	0.002	0.000
95–100°F day	(2)	**-0.001†**	**-0.087**	**11.529**	**-0.010**	**0.000**
95–100°F day	(3)	**-0.002***	**-0.163**	**9.784**	**-0.016**	**0.001**
100–105°F day	(1)	0.001	0.074	15.840	0.012	0.000
100–105°F day	(2)	**-0.001***	**-0.066**	**18.618**	**-0.012**	**0.000**
100–105°F day	(3)	**-0.001***	**-0.126**	**15.159**	**-0.019**	**0.000**
>105°F day	(1)	0.000	0.010	15.132	0.001	0.001
>105°F day	(2)	**-0.001****	**-0.114**	**16.625**	**-0.019**	**0.000**
>105°F day	(3)	**-0.001***	**-0.147**	**13.341**	**-0.020**	**0.000**
Model B. Number of heat days in trimester with cluster-specific thresholds						
90th–95th percentile	(1)	-0.0006	-0.064	4.447	-0.003	0.001
90th–95th percentile	(2)	**-0.0017†**	**-0.167**	**5.337**	**-0.009**	**0.001**
90th–95th percentile	(3)	**-0.0018***	**-0.182**	**4.362**	**-0.008**	**0.001**
95th–99th percentile	(1)	0.0003	0.030	5.454	0.002	0.001
95th–99th percentile	(2)	0.0010	0.100	6.306	0.006	0.001
95th–99th percentile	(3)	-0.0010	-0.096	5.203	-0.005	0.001
>99th percentile	(1)	-0.0002	-0.020	9.758	-0.002	0.001
>99th percentile	(2)	**-0.0007****	**-0.067**	**10.607**	**-0.007**	**0.000**
>99th percentile	(3)	0.0003	0.027	8.585	0.002	0.001
Model C. Proportion of heat days in trimester with absolute thresholds (count adjusted by trimester length)						
95–100°F day	(1)	0.0081	0.810	0.131	0.001	0.035
95–100°F day	(2)	-0.0700	-7.002	0.118	-0.008	0.043
95–100°F day	(3)	-0.0528	-5.280	0.137	-0.007	0.035
100–105°F day	(1)	0.0614	6.139	0.189	0.012	0.038
100–105°F day	(2)	-0.0422	-4.225	0.190	-0.008	0.027
100–105°F day	(3)	-0.0587	-5.873	0.212	-0.012	0.038
>105°F day	(1)	-0.0132	-1.320	0.180	-0.002	0.068
>105°F day	(2)	**-0.0930***	**-9.301**	**0.170**	**-0.016**	**0.026**
>105°F day	(3)	-0.0575	-5.754	0.188	-0.011	0.035
Model D. Proportion of heat days in trimester with cluster-specific thresholds (count adjusted by trimester length)						
90th–95th percentile	(1)	-0.0541	-5.412	0.053	-0.003	0.082
90th–95th percentile	(2)	**-0.1600†**	**-15.997**	**0.054**	**-0.009**	**0.081**
90th–95th percentile	(3)	**-0.1246***	**-12.464**	**0.061**	**-0.008**	**0.040**
95th–99th percentile	(1)	0.0252	2.517	0.065	0.002	0.057
95th–99th percentile	(2)	0.0986	9.860	0.064	0.006	0.105
95th–99th percentile	(3)	-0.0571	-5.708	0.073	-0.004	0.043
>99th percentile	(1)	-0.0163	-1.631	0.116	-0.002	0.070

>99th percentile	(2)	**-0.0648****	**-6.477**	**0.108**	**-0.007**	**0.013**
>99th percentile	(3)	0.0285	2.846	0.122	0.003	0.042
Model E. Excluding twins from specification A. – Count of heat days in trimester with absolute thresholds						
95–100°F day	(1)	0.0003	0.029	11.039	0.003	0.000
95–100°F day	(2)	**-0.0007†**	**-0.067**	**11.529**	**-0.008**	**0.000**
95–100°F day	(3)	**-0.0014***	**-0.143**	**9.784**	**-0.014**	**0.000**
100–105°F day	(1)	**0.0007†**	**0.072**	**15.840**	**0.011**	**0.000**
100–105°F day	(2)	-0.0005	-0.052	18.618	-0.010	0.000
100–105°F day	(3)	**-0.0009***	**-0.092**	**15.159**	**-0.014**	**0.000**
>105°F day	(1)	0.0004	0.043	15.132	0.007	0.001
>105°F day	(2)	**-0.0008***	**-0.083**	**16.625**	**-0.014**	**0.000**
>105°F day	(3)	**-0.0013***	**-0.128**	**13.341**	**-0.017**	**0.000**

Notes: Results for a linear probability estimating prenatal heat impacts on infant mortality using different heat exposure measurement. Outcome defined as the infant's death before reaching its first birthday. Heat thresholds in models B. and D. are based on the cluster-specific daily maximum temperature distribution from 1993–2018. Heat thresholds in model A., C., and E. apply absolute thresholds (95–100°F, 100–105°F, >105°F or in degrees Celsius 35–37.78°C, 37.78–40.56°C, >40.56°C). Heat exposure variables in models C. and D. measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds, divided by the total number of days in the gestational trimester to adjust for variation in gestational length among infants. All models are estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth (12–20; 21–34; 35+ years), maternal education (no; primary; secondary/higher education), the mother's most recent husband's or partner's education (no; primary; secondary/higher education), marital status, urban/rural status of the cluster, birth order (1; 2; 3; 4; 5+) and infant sex (male = 1). For further information on data and modelling, please refer to section 3–5. Baseline probability of infant death in the analytical sample is 0.0494 (or 49.4 per 1000). Number of observations and model fit statistics: Model A.: N = 9,016, Adj. R2: 0.016, Within R2: 0.011; Model B.: N = 9,016, Adj. R2: 0.013, Within R2: 0.008: Model C.: N = 9,016, Adj. R2: 0.014, Within R2: 0.009; Model D.: N = 9,016, Adj. R2: 0.013, Within R2: 0.008; Model E.: 8,689, Adj. R2: 0.012 Within R2: 0.009

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Appendix Table 2: Distribution of gestational length (in completed months) for children of the respondent in the five years prior to the interview, Source: Mali DHS 2018

Gestational duration in completed months	Frequency	Percentage
4	2	0.02%
5	2	0.02%
6	3	0.03%
7	62	0.69%
8	66	0.73%
9	8665	96.03%
10	223	2.47%
/	9,016	100,00%

N= 9,016

Appendix Table 3: Results from a logistic regression estimating the effect of prenatal heat exposure in each trimester on infant deaths

Heat exposure	**Trimeste r**	**β (Log odds)**	**Odds ratio**	**Percentage change**	**SE**
95–100°F day	(1)	0.003	1.003	0.290	0.008
95–100°F day	(2)	**–0.019***	**0.981**	**–1.890**	**0.008**
95–100°F day	(3)	**–0.031****	**0.969**	**–3.093**	**0.008**
100–105°F day	(1)	**0.016†**	**1.016**	**1.622**	**0.008**
100–105°F day	(2)	**–0.014†**	**0.986**	**–1.417**	**0.008**
100–105°F day	(3)	**–0.024****	**0.976**	**–2.412**	**0.008**
>105°F day	(1)	–0.001	0.999	–0.050	0.009
>105°F day	(2)	**–0.025****	**0.975**	**–2.496**	**0.008**
>105°F day	(3)	**–0.028***	**0.973**	**–2.713**	**0.011**

Notes: Results for a logistic regression model estimating prenatal heat impacts on infant mortality. Outcome defined as infant's death before reaching its first birthday. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects. Controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth (12–20; 21–34; 35+ years), maternal education (no; primary; secondary/higher education), the mother's most recent husband's or partner's education (no; primary; secondary/higher education), urban/rural status of the cluster, birth order (1; 2; 3; 4; 5+), and infant sex. For further information on data and modelling, please refer to section 3–5. N = 9,016, Null deviance: 3533.6 on 9015 df, Residual deviance: 3164.1 on 8836 df, AIC: 3524.

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Appendix Table 4: Results from a linear probability model estimating the effect of heat exposure during gestation on the probability of pregnancy ending in termination

Heat exposure	β	SE	SD of predictor	Change in pregnancy termination probability for a 1-SD increase in heat exposure
95–100°F day	0.05	0.20	0.07	0.004
100–105°F day	**0.64****	**0.14**	**0.10**	**0.063**
>105°F day	**0.35***	**0.11**	**0.11**	**0.039**

Notes: Results for a linear probability estimating prenatal heat impacts on pregnancy termination. Percentage point change in the probability of the pregnancy ending in termination for one additional heat day in gestation with 95% confidence intervals. Outcome defined as the pregnancy ending in a termination (miscarriage, stillbirth, abortion). Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. For further information on data and modelling, please refer to section 3–5. *Sources*: Mali DHS 2018, ERA5-Land; *N* = 9,016, Adj. R2: 0.089, Within R2: 0.065.

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Appendix Supplementary information on the analysis for Figure 3

Unfortunately, the DHS pregnancy termination data is limited in detail. A first limitation is that the questionnaire does not distinguish between induced abortions and unintended pregnancy losses (i.e. miscarriages and stillbirths), while our hypothesis is only focused on heat-triggered unintended pregnancy losses. Unintended pregnancy loss risk is globally estimated at 10-15% of all pregnancies (Quenby et al. 2021), whereas induced abortion prevalence is lower, estimated in Mali at 8.9% per year over the period between 2015 and 2019 (Guttmacher Institute 2021)[35]. In addition, Mali's abortion policies are restrictive and include sanctions[36], potentially making respondents less likely to report induced abortions because of cultural norms, fear of repercussions and stigma (Tourangeau & Yan 2007). However, even if the variable captures also induced abortions, this would likely lead to an underestimation of the effect of heat on pregnancy losses: The combined measurement of spontaneous and induced abortions could lead to an overestimation of the effect of heat on spontaneous abortions, if heat exposure increases both spontaneous and induced abortions. Existing evidence instead suggests that extreme heat may decrease induced abortions rather than increase them (Abdel Ghany et al. 2024). In this case, the estimated positive effect of extreme heat on spontaneous abortions would be an underestimation, as an increase in total abortions under heat exposure is even more likely to be driven by increases in spontaneous abortions.

We also find no correlation between socioeconomic status (i.e. maternal education) and recorded pregnancy termination that would point to the variable particularly capturing induced abortions (under the assumption that higher-socioeconomic status individuals have better access to induced abortion). Despite valid concerns including the lack of distinction between induced and spontaneous abortions and strong interviewer effects in the DHS on this part of the questionnaire (Leone et al. 2021), the DHS remain the primary data source for nationally representative data on abortions alongside birth histories and sociodemographic characteristics of the respondent in Mali. A second limitation of the DHS pregnancy termination data lies in its self-reported nature: early pregnancy losses are often underreported, as they can be difficult to detect despite frequently occurring in the first weeks of gestation (Dellicour et al. 2016). However, we do not regard this as a threat to the validity of our results, as any underreporting of early pregnancy losses would likely underestimate the impact of heat exposure on pregnancy loss.

Our analysis is restricted to the respondent's last pregnancy to account for potential selection bias in the non-live birth sample. While *all* live births of the respondent in the five years prior to the interview are recorded, only *a maximum of one* pregnancy termination is recorded for the same time interval, even if the respondent had multiple terminations. For the respondents that ever had a pregnancy termination, the month and year of termination and the pregnancy duration (in months) are recorded – but only for their most recent pregnancy termination. To address this selection of non-live births, we restrict the pool of all recorded pregnancies to include only the respondent's *last*

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[35] The Guttmacher Institute (2021) estimates the annual abortion prevalence in 2015–2019 to be 23 per 1000 women in reproductive ages 15-49, or 92,600 abortions of 1,040,000 pregnancies in total per annum (8.9%).

[36] Induced abortions are legally permitted in Mali only to save the mother's life and in cases of incest and rape. Under other conditions, abortion providers and assisting individuals can be sanctioned. (WHO 2017)

pregnancy – i.e. we construct a dataset where there is only one birth per respondent, which is their most recent birth (whether live or non-live birth)[37].

The treatment variables are analogous to the main analysis but aggregated for the whole pregnancy rather than capturing heat exposure in each trimester of gestation. Hence, the treatment variables capture the number of days in the gestation where the daily maximum temperature fell into each of the three heat bins (95–100°F, 100–105°F, >105°F). The gestational period is approximated using the recorded survey information on pregnancy duration for the termination (measured in months). Missing pregnancy durations for terminations are imputed with the terminations' median pregnancy duration of 84 days.

[37] This means that a) if the recorded pregnancy termination took place after the last livebirth, we include only the pregnancy termination; b) if the respondent had a livebirth after the pregnancy termination, only the most recent livebirth is included; and c) if the respondent did not have a pregnancy termination in the five years prior to the interview, only their most recent livebirth is included.

Appendix Table 5: Distribution of gestational length (in completed months) for pregnancies that are the respondent's last pregnancy and resulted in a pregnancy termination, Source: Mali DHS 2018

Gestational length (in completed months)	Frequency	Percentage (of all last pregnancies, including live births and non-live births)
1	13	0.098%
2	27	0.205%
3	37	0.280%
4	17	0.129%
5	7	0.053%
6	4	0.030%
7	5	0.038%
8	4	0.030%
9	18	0.136%
Total non-live births	132	100%

Notes: Total last pregnancies (live birth and non-live birth): N=5,840

Appendix Table 6: Results from a negative binomial model estimating the effect of heat exposure during gestation on the number of antenatal care visits for the pregnancy

Heat exposure	**β (Log of count)**	**Factor Change (Exp(β ¿¿**	**Percentage change**	**SE**
95–100°F days	**–0.002†**	**0.998**	**–0.175**	**0.001**
100–105°F days	**–0.002***	**0.998**	**–0.212**	**0.001**
>105°F days	–0.001	0.999	–0.131	0.001

Notes: Fig. 5: Results for a negative binomial model estimating gestational heat impacts on antenatal care visits. Percentage change in the number of antenatal care visits for the pregnancy for one additional heat day in gestation with 95% confidence intervals from a negative binomial model. Outcome defined as the number of antenatal care visits. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *N* = 5,559, Null deviance: 9579.1 on 5726 df, Residual deviance: 7928.6 on 5558 df, AIC: 24199, 2 x log-likelihood: -23859.228.

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Appendix Table 7: Results from a linear probability model estimating the effect of heat exposure heat exposure in each gestational trimester on infant size at birth

Heat exposure	**Trimester**	β	**Percentage point change**	**SE**
95–100°F day	(1)	0.0017	0.166	0.001
95–100°F day	(2)	0.0014	0.143	0.002
95–100°F day	(3)	**0.0066***	**0.664**	**0.002**
100–105°F day	(1)	–0.0028	–0.277	0.002
100–105°F day	(2)	–0.0002	–0.024	0.002
100–105°F day	(3)	0.0013	0.128	0.002
>105°F day	(1)	–0.0010	–0.099	0.001
>105°F day	(2)	0.0009	0.093	0.002
>105°F day	(3)	0.0014	0.136	0.002

Notes: Results for a linear probability estimating prenatal heat impacts on infant size at birth. Percentage point change in the infant's size at birth for one additional heat day in each gestational trimester with 95% confidence intervals. Outcome defined as the infant's size at birth based on maternal perception with categories: 1) very small, 2) smaller than average, 3) average, 4) larger than average, 5) very large. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. N = 9,016, Adj. R2: 0.030, Within R2: 0.009.

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Appendix Table 8: Results from a linear probability model estimating the effect of heat exposure heat exposure in each gestational trimester on birthweight and low birthweight

Heat exposure	Trimester	β	SE
A. Birthweight (g)			
95–100°F day	(1)	2.89	2.63
95–100°F day	(2)	-1.68	3.52
95–100°F day	(3)	**11.86****	**2.43**
100–105°F day	(1)	-5.03	3.83
100–105°F day	(2)	-2.87	4.61
100–105°F day	(3)	5.61	4.63
>105°F day	(1)	**-11.49***	**4.27**
>105°F day	(2)	**-8.93†**	**4.46**
>105°F day	(3)	-5.12	6.60
B. Low Birthweight (<2,500g)			
95–100°F day	(1)	-0.0017	0.0013
95–100°F day	(2)	0.0013	0.0013
95–100°F day	(3)	**-0.0051****	**0.0012**
100–105°F day	(1)	0.0003	0.0017
100–105°F day	(2)	-0.0001	0.0005
100–105°F day	(3)	**-0.0035†**	**0.0018**
>105°F day	(1)	0.0026	0.0018
>105°F day	(2)	0.0010	0.0014
>105°F day	(3)	-0.0000	0.0009

Notes: Results for a linear probability estimating prenatal heat impacts on birthweight in grams (Panel A) and low birthweight (Panel B), defined as <2,500g. Percentage point change in the outcome for one additional heat day in each gestational trimester with 95% confidence intervals. Heat exposure variables measure the number of days in the gestational trimester where the daily maximum temperature falls into the specified heat thresholds. Model is estimated with region-by-calendar-month-of-birth and region-by-calendar-year-of-birth fixed effects and controls for the average amount of rainfall at the cluster location in each trimester, maternal age at birth, maternal education, the mother's most recent husband's or partner's education, marital status, urban/rural status of the cluster, infant birth order, and infant sex. *N* = 9,016, Adj. R2: 0.030, Within R2: 0.009.

Sources: Mali DHS 2018, ERA5-Land

†p < .10; *p < .05; **p < .01

Chapter VI: Discussion

Co-authorship note: This chapter is based on solo-authored work and co-authored work. All sections are based on solo-authored work, except Section 1.

Section 1 (Ethical and practical considerations after the DHS Program's termination) draws on first-authored work with co-authors. The co-authors are Aasli A. Nur[1,2,3], Kerry L.D. MacQuarrie[4], Joshua K. Wilde[1,2,5,6,7], Elizabeth A. Sully[8], Mahesh Karra[9], Ursula Gazeley[1,2], Ben M. John[5,10], Livia Montana[11,12].

I conceptualized the article and wrote it. Joshua Wilde and Livia Montana contributed to the conceptualization. Aasli Nur conducted a bibliometric analysis. All co-authors provided comments and writing edits.

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Our opinion article with the title "Moving towards equitable data infrastructure and research integrity after the termination of the DHS Program" is available publicly as a preprint (https://doi.org/10.31235/osf.io/ka3r5_v1). The preprint discusses the implications of the DHS Program's termination for research in demography, public health, and other disciplines more generally. The work is based on collaboration between demographers, economists, epidemiologists, and the former Deputy Director of the DHS Program (Livia Montana) and Director of Research (Kerry MacQuarrie).

However, for this chapter, I have changed the scope of the article and adapted it to specific issues in climate-population research. Based on the preprint to which co-authors contributed as described, Section 1 in this chapter was entirely written by myself without contributions from co-authors.

Publication note: This work is currently unpublished, besides the above-mentioned preprint. As of 18 July 2025, the preprint has received almost 1,000 views since its publication on 23 May 2025.

Chapter VI: Discussion

1 Ethical and practical considerations after the DHS Program's termination

1.1 Contextualizing the DHS Program's termination

The DHS Program's termination in 2025 has created significant uncertainty for global health and demographic research, with important implications for climate-population inquiry. New access requests for DHS data are no longer being reviewed or granted since the termination. In this section, I reflect on the role of DHS data for this field of research, and on ethical and practical issues associated with the program's termination.

In January 2025, executive orders by President Trump led to the termination of the Demographic and Health Survey (DHS) Program through the dismantling of the United States Agency for International Development (USAID) and a proposed reduction in US foreign development assistance by 84% for 2026 (United States Department of State 2025; The White House 2025). The program's global influence means that its termination will drastically limit what we can know about population health and development (Grown 2025), and climate impacts in LMICs. In the context of a wide-ranging undermining of health and demographic data infrastructure due to the unprecedented funding cuts in US foreign assistance, these shifts in knowledge and capacity will continue to impact the research and policy landscape in these fields for years to come.

The DHS has been one of the most authoritative data sources on population health and global development in low- and middle-income countries (LMICs) and constitutes a unique data source for climate-birth linkages in LMICs, as argued in Chapter II. The DHS combine crucial properties for climate-health research in LMICs. They offer a) micro-level data on births, b) alongside sociodemographic characteristics of the mother and household, c) which are georeferenced to allow for environmental linkage, d) harmonized across a large set of countries, and e) generally of high quality and f) (sub-)nationally representative. DHS surveys collected information on a range of demographic, maternal, and infant health topics (The DHS Program, n.d.-b), facilitating the analyses of a broad range of climate linkages for different demographic and health outcomes.

The termination of the DHS Program leaves a void of information and uncertainty around whether DHS data will continue to be available, the ethical and legal issues around how to treat individually held DHS datasets, and how climate impacts can be studied in LMICs going forward. I argue that there are serious legal, ethical, and practical pitfalls associated with the informal dissemination of DHS data. While the future of existing DHS datasets remains in flux with many stakeholders interested in preserving this resource, the global health and demographic research community should diversify its use of data sources, invest in strengthening data infrastructure in LMICs, and share data management and use practices publicly to accelerate research progress.

In light of fears that a *dark age* for health data may be looming for LMICs (Khaki et al. 2025), identifying how climate researchers should navigate the sudden void is urgent. The loss of this data infrastructure is widely perceived as a threat to health and development progress and the regular monitoring of population health and wellbeing of the most vulnerable populations of the world (Väisänen et al. 2025; do Rio Sales 2025). These concerns are important considering the growing risks climate change poses to LMIC populations. An objective of the DHS Program was to facilitate the collection and use of data by LMICs for evaluation and policy decision-making. Since the DHS Program's launch, more than 9,000 studies, reports, and book chapters[38] have been published based on more than 400 DHS surveys that were conducted in 91 countries (Abdel Ghany et al. 2025). The DHS has been instrumental in improving the evidence base for health policies and interventions, particularly in Sub-Saharan Africa and Central and Southern Asia (ibid.). Particularly in these regions insight on climate-population linkages is urgently needed to develop evidence-based and targeted climate adaptation policies.

[38] Figure produced by Aasli A. Nur through a bibliometric analysis as part of the co-authored article, as cited.

1.2 Advancing climate-population research after the DHS Program's termination

Regardless of whether and how stakeholders reimagine and rebuild the DHS Program through a new model, I argue that its recent termination is a pivotal moment that opens new possibilities to rebuild data infrastructures and networks in an equitable way. This process can create new opportunities for climate-population research.

The end of the DHS Program offers a long-anticipated opportunity to decolonize and recenter data infrastructure and capacity in LMICs, after decades of being administered from the US, and partly funded by USAID. LMIC stakeholders have prominently called for the decolonization of climate and climate health research (Deranger et al. 2022; Hoogeveen et al. 2023), building on the legacy of the decolonization movement in global health research. Yet, in the demographic discipline authors from LMIC institutions are starkly underrepresented – although their populations face the largest climate change burdens. Environmental high-resolution raster data is demanding to download, store, and process. To overcome these barriers, the global research community should strategically intensify investments into lasting data collection, research infrastructure, and training efforts that are led by institutions in LMICs. In a new model of the DHS, a small core initiative is still critical to ensure standardization of survey methodology and data harmonization globally. This is also relevant for ensuring standardized geolocation information that allows for environmental data linkage. Coordination will also be critical to ensure continued data availability.

Importantly, I encourage climate-population researchers to consider utilizing data from pre-existing but under-utilized data sources of high quality. These include the Health and Demographic Surveillance Systems (HDSS), census microdata files (such as those available through IPUMS), UNICEF's Multiple Indicator Cluster Surveys (MICS), the Young Lives Study, the Living Standards and Measurement Study's Integrated Surveys on Agriculture (LSMS-ISA), routinely collected national health system data (e.g., Health

Management Information System (HMIS) data), and countless nationally led data collection efforts. These data sources should be consistently made available. Their increased use can both diversify the data sources used in climate-population studies in LMICs and advance tools and methods in contexts where health and demographic data are limited. Such a shift also has the potential to diversify the research topics under investigation, the hypotheses that can be tested, and the methodologies that can be employed.

Furthermore, researchers should make their methodologies publicly available to facilitate reproducibility of climate-population research. Particularly valuable would be for researchers to contribute code for analyses that innovatively link DHS with environmental data and other data sources. While important advancements have been made, particularly in general science journals, the application of open science approaches still deserves further expansion. Only in this way can the field produce data-intensive studies with a cross-national perspective at rapid speed.

1.3 Dissemination of DHS copies: Ethical and practical issues

Due to its abrupt termination, researchers cannot request new access to DHS data anymore. How should they handle individually-held copies of DHS datasets? Crucially, there has been no change to the terms of use (https://dhsprogram.com/data/Terms-of-Use.cfm) governing DHS data use and dissemination – researchers are still bound by the original agreement they accepted when granted access, even though the DHS Program is no longer operational. Several ethical issues must be considered.

DHS users are acutely aware of the many hours respondents spend in time-intensive interviews, and the financial and organizational resources national statistical offices invest in the large-scale collection of these data. Data users may fear that these tremendous investments could go to waste if the data are not available. Respondents have provided informed consent with the expectation that their data be used to improve population health and well-being. Therefore, researchers may perceive an ethical responsibility toward respondents to continue DHS use, particularly in the face of growing climate risks. Researchers may also argue that sharing DHS data freely serves open science and removes access barriers.

Nonetheless, I advise against sharing existing datasets informally to protect respondents' and national statistical offices' rights and avoid academic misconduct. Individual researchers lack the legal right to share DHS data with other researchers, per the terms of use they entered into when they obtained rights to access the data. Only national statistical agencies, who own the data, have that right. Many researchers assume that the continued use of the DHS is in the interest of the respective national statistical agencies and their populations. Researchers should be aware that sharing data with other researchers without authorization by national statistics offices, however well-intentioned, may violate the rights of these agencies and of respondents.

Furthermore, the line between justified and unjustified use could be blurred by the lack of a formalized mechanism that centrally regulates who can and cannot gain access to DHS data. This raises new concerns around actors accessing data on sensitive topics for unapproved purposes. For example, the DHS Program's terms of data use prohibit use of the data for marketing and commercial purposes (The DHS Program, n.d.-a). A governance structure that would standardize procedures of access and withdrawal of consent is now absent, potentially putting the interests of respondents and national statistical offices at risk.

In addition to the legal and ethical concerns, informally disseminating DHS data may also give rise to severe practical issues of errors and misuse. Sharing data freely in informal networks enables both accidental and malicious data manipulation. Since the unique original data source is not centrally accessible and a central mechanism to report and correct errors in the original database no longer exists, there is little to no standardized quality or version control. This not only opens the door to manipulation of both data and research findings on sensitive topics, which will be difficult to track, but it also closes the door to credible reproducibility.

Serious concerns around equity of access further aggravate the matter. Dependence on informal research networks to access DHS data would likely disadvantage researchers from marginalized backgrounds, users from LMICs, early-career scholars, and other researchers whose career networks are limited. An informal dissemination mechanism may therefore reinforce existing inequalities in data availability and representation in scientific discourse.

Researchers have permission to use DHS data only for previously registered studies and projects. Unregistered projects lack the legal (and, by extension, ethical) foundation necessary to justify its use: an approved data access request. To use the data for another purpose, researchers have "[agreed] to submit a new research project request" (The DHS Program, n.d.-a). Having manually approved data access requests to avoid misuse to date, the DHS Program can, since its termination, no longer approve new project requests or modifications to existing projects. In practice, this implies that the use of data for purposes unrelated to registered projects can be *unauthorized* use that fails to meet minimum legal requirements. Additionally, the untargeted downloading of data also violates the principle of "data minimization," which urges researchers to only collect necessary data to reduce privacy risk, enhance efficiency, and ensure ethical compliance.

This prompts a question that reveals how grave the consequences of mismanaging the current data landscape would be: If we resort to sharing DHS data freely and informally now, what was the point of ever having a mechanism through which data access could be granted and denied? Unregulated sharing of DHS data threatens to undermine the legitimacy of all previously approved data access requests since the program's inception decades ago. By sharing data informally and using it without authorization, researchers run the risk of corroding principles of research integrity that compel them to protect property rights and prevent data misuse.

1.4 Conclusion

Given the risks of sharing datasets informally outside of researchers' data use agreements, there is an urgent need for a new initiative to reiterate country ownership and re-establish rights for redistribution with all countries where DHS data were collected and resume processing researcher requests to access the data. In the meantime, researchers, data users, and stakeholders should abide by the terms of use and refrain from distribution that violates those agreements and best scientific practices. The legitimacy of scientific studies to improve population health in LMICs under climate change crucially depends on researchers' individual responsibility to consistently uphold ethical and legal standards of data access. In addition, climate researchers should seize the opportunity to not only explore underutilized data sources, but also seek to provide input into how new data collection efforts can overcome existing limitations of the DHS to reimagine future climate research.

2 Emerging lessons

2.1 Objective 1: To investigate early life mortality in the context of in-utero temperature exposure

This thesis moved beyond the literature's current focus on old-age mortality (Matthews et al. 2025) and centered the investigation of temperature impacts on early life mortality, more specifically prenatal and infant mortality. Chapter IV finds that extreme heat reduces the SRB. SRB changes should be driven by either a) sex-biased pregnancy loss, or b) sex-biased changes in induced abortion. The findings show that in Sub-Saharan Africa, a sex-biased pregnancy loss response is most likely at play, as opposed to India, where changes in sex-selective abortion may occur. Through both spontaneous and induced abortion mechanisms, extreme heat affects prenatal mortality. Furthermore, Chapter V finds that prenatal heat exposure reduces mortality in the first year of life. Together these findings show that extreme heat can induce intensified male-biased prenatal mortality, which results in lower infant mortality, complementing existing research on the adverse effects of heat on adult mortality. In addition, the findings underline that extreme heat not only affects mortality outcomes for postnatal exposures, but already in the prenatal period.

2.2 Objective 2: To identify in-utero temperature impacts on population composition

This thesis identified in-utero temperature impacts on population composition *at* birth and *after* birth. First, the findings demonstrate that population composition at birth can be impacted by prenatal temperature exposure in diverse LMIC contexts, even if heterogeneity patterns and pathways differ. More specifically, Chapter IV shows that temperature above 20°C reduces the sex balance at birth (i.e. fewer males) in Sub-Saharan Africa and India. The magnitude of these reductions is sizable. In Sub-Saharan Africa, a 1-SD increase in >30°C days during the second gestational trimester leads to 2.4 fewer male per 100 female births from a baseline of 103.4 male per 100 female births. Reductions are particularly pronounced for mothers in rural areas and high parity births, suggesting that the population composition of these groups is more sensitive to extreme heat compared to other sociodemographic groups. In India, reductions are particularly pronounced for mothers in northern states of India, and high parity births to sonless mothers. No reductions are apparent for other groups. This suggests that a decrease in induced sex-selective abortion could be driving the male birth reductions in this country. Though through different mechanisms, both regions exhibit a change in the sex balance at birth after prenatal heat exposure.

Furthermore, Chapter V shows that prenatal heat exposure can also impact population composition *after* birth, in infancy. Several studies had linked prenatal heat exposure with both outcomes at birth and in adulthood (Isen et al. 2017; McElroy et al. 2022; Wilde et al. 2017). But this thesis addressed a gap in the literature by providing new evidence that prenatal heat exposure can affect outcomes in the first year of life. In Mali, where heat impacts can be disentangled from other environmental drivers of infant health, I observed statistically significant reductions in infant mortality. The direction of this effect – lower infant mortality – is in line with previous studies finding that prenatal heat exposure leads to *improved* educational outcomes in adulthood in Sub-Saharan Africa (Wilde et al. 2017) and lower infant mortality in LMICs (Geruso and Spears 2018). But it seemingly contradicts studies in the US and Ecuador finding *worse* socioeconomic attainment in adulthood (Fishman et al. 2019; Isen et al. 2017). While all studies identify a link between prenatal heat exposure and outcomes after birth, the direction of this effect may be shaped by contextual factors, which are yet to be identified. Additionally, it could be tested whether the observed advantage in the first year of life is short-lived, which could suggest prenatal scarring effects become apparent at later ages.

To address objective 2, this thesis provides evidence that prenatal heat exposure impacts the SRB and infant mortality – two population composition outcomes that have been understudied in the literature on environmental impacts.

2.3 Objective 3: To identify social stratification in the impact of in-utero heat exposure in LMICs

The thesis highlights important inequities in the impact of extreme heat on health between LMIC populations. To achieve this objective, the thesis analyzed the impact of in-utero temperature exposure on ANC visits, SRBs, and infant mortality, testing differences between world regions, countries, and social groups. As stratifying variables, I considered both biological factors, such as maternal age and infant sex, as well as social and socio-cultural factors, such as education, country-specific measurements of wealth, urban-rural differences, and female empowerment in household decision-making.

From a range of population contexts, I identified Sub-Saharan African populations as particularly vulnerable to extreme heat impacts. This vulnerability is apparent for both health-related behaviour and the physical health of pregnant mothers. In my sample of 52 countries where DHS surveys were conducted, Sub-Saharan Africa was the only world region where extreme heat leads to fewer ANC visits (Chapter III). This is corroborated by my findings on the country level, where only African countries show ANC reductions. By contrast, extreme heat has the opposite effect in Latin America and the Caribbean. Here, extreme heat leads mothers to have more ANC visits, indicating that they may be able to intensify healthcare visits. Besides these behavioural adaptations, I showed in Chapter IV that mothers in Sub-Saharan Africa are particularly vulnerable to the physiological impacts of heat in terms of heat-induced pregnancy loss. To contextualize these findings, it should be noted that populations in Sub-Saharan Africa not only suffer from disproportionate vulnerability to climate change (Calvin et al. 2023) but also have some of the world's lowest levels of ANC coverage (UNICEF 2024).

Turning to differences between social groups, my findings indicate that disadvantaged mothers face disproportionate impacts of extreme heat on health within Sub-Saharan Africa. Regarding SES differences, I showed that reductions in both male birth (Chapter IV) and ANC visits (Chapter III) are larger for mothers with no or only primary formal education, compared to mothers with secondary or higher educational attainment. Reductions in ANC visits are also more pronounced for mothers who report that getting money to go to the health facility is a problem, unlike mothers who report that this is no problem for them. Regarding differences by healthcare access, the findings show that mothers who already struggle with general healthcare access because of distance and transport experience substantial ANC reductions under heat. These reductions are not apparent for mothers with better general healthcare access. Indicators of female empowerment, measured by involvement in household decision-making, are less salient factors in shaping the impact of heat on ANC. In summary, these findings point to the importance of inequities in healthcare access and infrastructure, beyond SES-related disadvantage.

However, the findings also show that for social-biological factors, heterogeneity patterns can not only be context-specific, but also outcome specific. Overall, few differences by maternal age are apparent, and some differences by parity. But the direction of the gradient differs between SRBs and ANC. The SRB – as the more biological health outcome – shows that especially high birth orders (four and higher) are disproportionately affected. ANC visits – as the more behavioural outcome – instead suggest that low birth orders are disproportionately affected. Importantly, these results suggest that heterogeneity responses can differ between outcomes, even for outcomes of the same underlying sample.

Applying a reproductive justice lens, the reproductive (health) disadvantage low SES mothers and high parity birth orders face because of extreme heat is concerning. Given that male birth reductions are most likely driven by pregnancy loss, disadvantaged mothers not only face disproportionate burdens on health considering that pregnancy loss can pose immense risks for physical and mental health (Quenby et al. 2021). Extreme heat may also make disadvantaged mothers disproportionately less able to conceive, experience live births, carry pregnancies to term, and give birth to healthy neonates. Ultimately, the pronounced male birth reductions for high parity births raise concerns whether extreme heat could impair mothers' ability to achieve desired fertility levels. This question warrants further attention.

From a conceptual perspective, a further emerging lesson from these heterogeneity analyses is that they can be helpful both when heat impacts are identified and unidentified in the main (pooled) sample. When heat impacts are identified, heterogeneity analyses can point to the subgroups that are most strongly affected and drive the main effect. Alternatively, such analyses can also yield consistent effects across groups that suggest impacts are experienced similarly. This can indicate a lack of resilience across all groups. In addition, information on whether there are group differences or consistencies can also help inform inference on mechanisms. Heterogeneity analyses across different sociodemographic characteristics indicate which mechanisms are important in shaping the relationship under study. Furthermore, even when there is a null finding for the pooled sample, heterogeneity analyses can uncover masked inequities. Conversely, such analyses can also rule out that this is the case, at least for the observed variables used in such tests.

The thesis presented a strategy for making temperature effects comparable across samples. First, the coefficients from different samples in Chapter III to V represented the change (expressed either as percent or percentage point changes, depending on the model) in the outcome for one additional heat day during gestation. But additionally, I took into account that there can be significant variation in how likely a 1-day increase in heat days is across samples. For this reason, I translated the effects for a 1-day increase into the effect for a 1-SD increase in heat exposure days in gestation. This approach makes results comparable across geographic regions and social groups, while also offering an alternative interpretation that is context specific.

Overall, the findings indicate that temperature impacts on maternal health may be most pronounced in contexts where mothers are already disadvantaged. Given that extreme heat is increasing in frequency and intensity, especially in LMICs (Calvin et al. 2023), and affects disadvantaged mothers disproportionately, it has the potential to widen existing global and within-country reproductive (health) inequalities.

2.4 Objective 4: To identify mechanisms that link temperature exposure and the outcomes

Theoretical contributions

The thesis made important theoretical contributions to the literature by identifying biological and behavioural mechanisms. Synthesizing these mechanisms across the empirical chapters, three main pathways emerge that explain temperature impacts on maternal and infant health outcomes:

a) Intensified spontaneous abortion

b) Reduced induced sex-selective abortion

c) Changes in ANC

Extreme heat may (a) intensify spontaneous abortion, as findings across Chapter IV and V indicate. This has consequences for mothers as they have an elevated risk of experiencing pregnancy loss, infants as they may experience better health after birth, and the composition of the population because of changes in cohort selection and sex structure. In Chapter IV, I argued that SRB changes can be driven by either male-biased pregnancy loss or changes in sex-selective abortion behaviour. In Sub-Saharan Africa I found that in-utero temperature exposure lowers male births. Given that sex-selective abortion is unlikely to shape SRBs in this region, extreme heat most likely intensifies male-biased pregnancy loss. This also has consequences for infant health (Chapter V). Here, I observed that in-utero exposed infants have lower mortality in the first year after birth. This indicates that in-utero temperature exposure has consequences for infant health postnatally, in line with existing evidence on educational attainment (Fishman et al. 2019; Isen et al. 2017; Wilde et al. 2017). Both chapters also identified that the heat-induced spontaneous abortion mechanism shapes population composition changes. Extreme heat may make newborn cohorts less male and positively selected on health.

Extreme heat may also impact maternal health and population composition by (b) reducing induced sex-selective abortion. Chapter IV showed that in India male birth reductions in response to extreme heat are most pronounced for the sociodemographic subgroups that have the highest propensity to sex-select, based on parity, age, region, and sibling sex composition. Direct data on sex-selective abortions is not available because such abortions are illegal. But heterogeneity patterns, the magnitude of effects, and the timing in the second trimester strongly suggest this mechanism is at play. At the same time, Chapter III showed that in India, temperature does not decrease ANC visits. Together, these findings indicate that extreme heat does not make mothers less likely to receive ANC but still less likely to sex-select because of other reasons than immobility under heat. These are novel insights into how abortion behaviour may change in the context of extreme heat, with relevance to both reproductive health and sex imbalances on the population level. Further context-sensitive work is needed to test whether extreme heat reduces induced abortions more generally, or only sex-selective abortions in India specifically.

A further mechanism that may drive the link between extreme heat and maternal health is changes in ANC visits, as findings in Chapter III showed. ANC visits are crucial for a positive pregnancy experience and to avoid pregnancy complications. Interestingly, the direction of the temperature effect on ANC is not uniform across geographic regions. In Sub-Saharan Africa, extreme heat reduces ANC visits. In Latin America and the Caribbean as well as in South and Southeast Asia, extreme heat increases ANC visits. In other regions, such as India, no ANC changes are observed. This suggests that extreme heat can shape health-related behavioural responses of mothers in highly context-specific ways. Mothers in disadvantaged regions may be particularly at risk. Further work should identify the factors that shape the direction of effects.

Methodological contributions

In manifold ways, I demonstrated how testing effect heterogeneity by a range of *sociodemographic* characteristics can advance our understanding of mechanisms. The key to inference about mechanisms here is that different mechanisms should induce different heterogeneity patterns by sociodemographic groups.

First, my study on heat exposure impacts the SRB (Chapter IV) exploited differences by maternal age, education, birth order, urban/rural residence, and the sex composition of prior births to show that the mechanisms of pregnancy loss in Sub-Saharan Africa and induced sex-selective abortion in India are most likely at play. Second, the thesis showed how even very limited information on sociodemographic characteristics can be leveraged for complex hypotheses. In Chapter V, infant mortality reductions after prenatal heat exposure should show different patterns by maternal SES depending on the mechanism: Mortality reductions should be 1) less pronounced for high SES mothers if driven by prenatal selection because of comparatively lower vulnerability, but 2) more pronounced for high SES if driven by compensatory maternal investment, which high SES mothers tend to provide more effectively (Hsin 2012). To gain insight on mechanisms, I used not only the gap between sociodemographic groups, but also the direction of the effects. Third, leveraging different types of sociodemographic characteristics can inform mechanisms. I showed in Chapter III that large reductions in ANC appear by mothers who report barriers in accessing healthcare, such as the distance and transport to the health facility – unlike by mothers who report no such problems. Hence, the heterogeneity analyses suggest that mobility impairment is a more important mechanism, compared to other mechanisms that could explain heat-induced ANC reductions but show no effect heterogeneity.

Beyond sociodemographic characteristics, my thesis also showcased how geographic and socio-cultural differences between different contexts can inform mechanisms. The socio-cultural difference I exploited in Chapter IV is on son preference norms and related sex-selective abortion practice between India and Sub-Saharan Africa. This cultural difference allowed me to test behavioural and biological responses to heat exposure comparatively between populations. The goal of leveraging the geographic context also applies to my work on Mali (Chapter V). Mali has unique geographic conditions that allow me to disentangle the effect of extreme heat from other infant health drivers (Grace et al. 2021).

My thesis also showed how testing sensitivity of different exposure windows in the gestational period can help uncover mechanisms, too. Chapter IV on SRBs achieves this. The study pinpoints likely exposure windows that should be particularly sensitive to heat, depending on the mechanism at play. Changes in sex-selective abortion should be most pronounced in the second trimester, because fetal sex detection is only possible from around the 14th week of gestation and later abortions in the third trimester have higher health risks. By contrast, existing literature suggests that heat-induced pregnancy loss should be particularly high in the first trimester (Barreca et al. 2018). While evidence is still emerging on sensitive exposure periods in the context of extreme heat, careful attention to timing can help in identifying heat-induced mechanisms.

Lastly, I showed how to exploit the magnitude of estimated effects between different subgroups to support inference about mechanisms. In Chapter IV on SRBs, the male birth reductions in India are much larger than in Sub-Saharan Africa. Given that Sub-Saharan African countries have much higher infant mortality rates (as a proxy for baseline health conditions), one would expect the opposite. Here, the magnitude of effects helps to distinguish mechanisms by making the pregnancy loss channel a less plausible interpretation of effects in India. In Chapter III on ANC, I showed that gaps between subgroups are largest for healthcare access related variables. Here, too, the magnitude of effects points to the most relevant mechanism.

2.5 Objective 5: To develop a methodological framework for temperature-birth linkage

The thesis presented a methodological framework for the linkage of high-resolution gridded environmental data with georeferenced, micro-level birth records from surveys, specifically from the DHS (Chapter II). The framework addresses the distinct methodological choices that are involved in choosing data sources, constructing measurements, and conducting analyses that aim to identify impacts of temperature variation on maternal and infant health that can be interpreted as plausibly causal.

First, I conceptualized how both *spatial* and *temporal* coverage and resolution guide the choice of data sources. To inform measurement construction where each birth’s in-utero conditions are captured, I described how to estimate the gestational window in the absence of detailed information. After defining the gestational period for each birth, I explained how gridded temperature data is extracted for each birth at the georeferenced community location and how to handle uncertainty in this point location. Next, I evaluated a range of inconsistently applied exposure measurement approaches in the literature. These include the use of mean vs. maximum temperature, absolute vs. relative temperature, and deviation measurements vs. temperature bins, among others. Though other measurement types may dominate the literature (Thiede et al. 2022; Gray and Thiede 2024), I argued for the use of absolute, progressive 5°C temperature bins that can reveal temperature effects on the outcome across different heat intensity levels. Lastly, the causal identification approach I defended in this chapter builds on work by Dell, Jones and Olken (2014) and Barreca, Deschenes and Guldi (2018). With concrete application to temperature-birth linkages, I explained their place-time fixed effects approach in the context of temperature impacts on maternal and infant health and discuss omitted variable bias from different sources. I extended the current literature by conceptualizing the role of parental characteristics as stratifying variables rather than confounders.

The resulting framework provides clear methodological guidance for the causal identification of temperature effects using micro-level birth records in LMICs, which I then applied rigorously in the empirical chapters (III–V). These applications illustrate how the use of absolute temperature bins and place-time fixed effects reveals temperature impacts across different heat intensities and geographic contexts. While the framework aims to be specific to the study of extreme heat impacts, the discussed issues are relevant to a range of environmental exposures and outcomes.

The consistent application of the developed methodological framework in this thesis revealed that the critical thresholds where temperature exposure affects maternal and infant health outcomes differ not only between study settings, but also between outcomes. Temperature affects ANC visits in Sub-Saharan Africa only for extreme levels – above 35°C and below 10°C. By contrast, in Latin America the ANC increases already appear at

30–35°C and increase in size for temperature above 35°C. While one might expect that similarly only extreme temperature levels affect the SRB, the method I use reveals that the SRB already decreases for mildly warm temperature above 20°C. The magnitude of SRB reductions remains uniform with rising temperature levels. This pattern points to a uniform biological response where male-biased pregnancy loss is triggered already at levels slightly above human thermal comfort. This contrasts with ANC visits, where the pattern indicates that behavioural responses may only be triggered at very high heat intensity, as mothers might only be deterred from seeking healthcare for their pregnancy under extreme conditions. These theoretical insights justify the use of temperature bins, which make few assumptions about relevant temperature thresholds.

2.6 Objective 6: To exploit different study settings in describing temperature impacts

The thesis demonstrated how the study's context can be chosen strategically to advance our understanding of how temperature affects maternal health, infant health, and population composition. The empirical chapters cover a global analysis (Chapter III), a comparative analysis across two regions (Chapter IV), and an in-depth single country study (Chapter V).

Viewing their findings in combination, the three approaches complement each other meaningfully. The *global* analysis is successful in describing how significantly the impact of temperature can vary across different world regions and countries. This approach helps to identify which populations may be particularly vulnerable to heat. The findings can motivate targeted interventions and stimulate further research into the individual and community level factors that buffer (or amplify) the effect of extreme heat. By contrast, the *comparative* approach exploits differences in social norms, climate, and population characteristics to test different types of explanatory pathways. This strategy helps highlight how the social and geographic context shape the relationship under study. Lastly, the *single-country* study narrows down general interest in a hypothesized relationship to a uniquely suitable case study. It provides an in-depth analysis of temperature impacts on infant mortality, taking climatic and social conditions into account, in a context where the hypothesized mechanisms are comparatively likely to be at play, and feasible to test. While Chapter V focused on Mali only, its findings have relevance to a broader context because they identify an underlying mechanism more clearly with more adequate data than would have been possible in other contexts. Single-country studies can therefore fill important gaps in our understanding on mechanisms that may be at play in a diverse range of settings, but more difficult to identify in others. In addition, single-country studies also inform policy and intervention by directly engaging with characteristics of a specific population.

In summary, global analyses help assess temperature impacts across a range of settings and point to vulnerable populations. But they are complemented by in-depth studies that explore concrete pathways across a range of settings, in both comparative and single-country studies. These studies can illuminate the specific relationship’s determinants, which can in turn inform tests across different contexts.

3 Limitations

The empirical work in this thesis has three main limitations, as outlined in the following. For limitations that are specific to each research study, I refer to Chapters III, IV, and V. In section 4 of this chapter, I suggest future directions of research based on these limitations.

First, in the empirical chapters on ANC and SRBs (Chapters III and IV), the gestational window is an estimated exposure period that involves uncertainty. Most georeferenced DHS surveys do not provide information on the day of birth and gestational length, but only the month of birth. This forces me to estimate the gestational window by using the month of birth and the prior eight to nine months as the gestational period. I discussed why preterm birth prevalence in LMICs can make a uniform standard duration of nine months as the exposure period across all pregnancies an issue in Chapter II, section 2. An alternative approach would be to focus only on DHS surveys where day of birth and gestational length information is available. However, this would drastically limit the available number of DHS surveys, excluding the very large 2020 India DHS among several others. A different alternative approach could be to approximate the gestational duration with the chosen approach (month of birth plus prior months) for the observations where more detailed information is lacking, and exploit day of birth and gestational length information for the other births. However, this would be time intensive as environmental data extraction and processing would need to be conducted with two different approaches. To the best of my knowledge, no study has examined whether different approaches to estimating the gestational length impacts study results in the context of temperature exposure. This would be an interesting contribution to assess how large potential biases are under either approach.

Second, my empirical chapters largely do not control for potential confounding from relative air humidity or model its moderating role. Humidity influences evaporation by dictating how much moisture content the ambient air can absorb. I do not control for humidity as I could not identify a data source that fulfilled temporal and spatial coverage demands for my survey data at the same spatial resolution. However, in Chapter IV on SRBs, I provided analyses in the appendix using WBGT, a combination of temperature and humidity. Here, I found that WBGT impacts are much less clearly identified than dry-bulb temperature effects. Given that I tested WBGT impacts across different contexts, the lack of identification might indicate that WBGT variation is a less salient environmental exposure. Nevertheless, future research should explore the role of humidity in the prenatal period for perinatal and postnatal outcomes. My analyses could be replicated using UTCI, WBGT, or humidity data, even if their spatial resolution differs from the NOAA and ERA5-Land temperature data I used.

Third, the identification of mechanisms in this thesis has limitations. The empirical work in this thesis focuses on important mechanisms that are testable with DHS data only. However, integrating survey and environmental data with other data sources, such as data on food insecurity or income, would open further avenues of research to test additional mechanisms. Furthermore, my studies focus on stratifying variables on the individual-level (i.e. the mother). This focus was chosen because some of the relationships under study have barely been investigated or not investigated previously. But meso- and macro-level factors, such as community characteristics, agricultural dependence, and health policies are likely to influence these relationships and should be considered in future studies. Lastly, the mechanisms tested are not directly observed but only inferred about (see Chapter I, objective 4). This limitation applies to many studies identifying climate impacts on reproductive and infant health, particularly studies in LMICs and studies using DHS data, and demands an exploration of underutilized data sources and strategic data collection efforts.

4 Emerging questions for future research

Based on the thesis's findings, several important questions emerge for future research on the intersection of temperature and populations. Addressing these questions will further advance our understanding of how temperature is linked with mothers' health and reproductive life-courses, infants' health and development across their life-course, and population composition and dynamics.

First, while the thesis identified that prenatal heat exposure may induce intensified prenatal selection, the consequences for population composition and dynamics require further insight. For example, extreme heat is associated with a lower sex balance. Does this sex balance persist into later ages? In addition, male birth reductions are most pronounced for birth orders four and higher. Since these reductions are most likely driven by pregnancy loss, the question arises whether heat-induced pregnancy loss is associated with completed fertility by posing a barrier to high parity births. This can be studied by disentangling quantum and tempo effects. Similarly, this thesis suggests prenatal heat exposure leads to an infant mortality advantage. How long lasting is this mortality advantage? My preliminary analyses suggest that the mortality advantage is only apparent in the first year of life, but not in the next four years. At the same time, several studies have linked prenatal heat exposure to health and socioeconomic attainment in adulthood (Fishman et al. 2019; Isen et al. 2017; Wilde et al. 2017). The effect of prenatal heat exposure on population composition at later ages deserves further attention across both high-income and LMIC settings.

Second, further work is necessary to understand which macro- and meso-level determinants shape the direction of temperature impacts across different contexts. My empirical work shows that extreme heat can both increase and decrease ANC visits in different contexts. Perhaps most importantly, context-specific factors such as healthcare infrastructure, policy, and social norms could shape the relationship. For example, a more developed healthcare infrastructure system with high coverage might enable mothers to intensify care-seeking behaviour when faced with environmental burdens. The role of these factors needs to be further explored to develop effective interventions. Ideally, this will involve moving beyond the focus on individual level determinants and innovatively incorporating data sources on health systems. Empirical work on the dominance of prenatal selection over scarring would also benefit from an incorporation of macro-level determinants. Heat-induced prenatal selection appears to be particularly strong in contexts with both poor baseline health and extreme levels of heat. But whether baseline health and climatic conditions indeed influence the intensity of heat-induced prenatal selection remains to be confirmed in comparative empirical analyses.

This thesis identified that the impacts of prenatal heat exposure are socially stratified, with large variations across world regions, countries, and social groups, but further scope to investigate the role of (dis)advantage exists. Evidence on the role of stratifying variables in temperature-birth relationships is overall still limited. For this reason, this thesis only focused on the role of maternal characteristics to provide first insight into how temperature impacts are socially stratified by individual level factors. However, a more multidimensional investigation of disadvantage would be valuable. Sociological theory on intersectionality (Crenshaw 1991) has found little application in climate-population studies, although it has been introduced to studies of health inequality and geography (Holman et al. 2021; Bambra 2022). Much reason exists to consider how inequalities intersect in the context of temperature exposure. These intersections could be based on rural-urban differences, locational vulnerability to heat, health infrastructure, race-ethnicity, SES, occupation, income and food insecurity, and many other factors that have been found to stratify heat exposure and impacts independently (Badakhshan et al. 2025; Ellena et al. 2020; Li et al. 2025; Rastogi et al. 2023). Future research should hence consider the intersection of disadvantages across a range of dimensions that shape mother's and infant's life-worlds.

A further question that has received very limited attention in the context of maternal and infant health is the role of physiological adaptation to heat. The mortality literature has produced evidence suggesting that some adaptation takes place as the populations' minimum mortality temperature can increase in the long-term (Yin et al. 2019; Folkerts et al. 2020). However, two gaps in the literature remain to understand adaptation in the context of reproductive health. The minimum mortality temperature might not necessarily translate into a "minimum prenatal mortality temperature" or a "maximum fertility temperature". First, pregnant individuals have specific demands on energy, hydration, and thermoregulation (Butte et al. 2004; Mulyani et al. 2021), warranting evidence that considers both limits to physiological adaptation and potential shifts in the minimum temperature for this population specifically. Second, how heat exposure in early life, adolescence, and reproductive ages could lead to increased resilience or vulnerability has not been investigated. Population level studies need to be complemented with epidemiological studies on thermal comfort of pregnant individuals and studies that consider heat adaptation across the life-course.

Lastly, findings from this thesis prompt new ideas about the role of extreme heat in producing social stratification. Much of the literature on a range of prenatal insults shows that such insults usually have lasting *negative* consequences on health and development throughout the life-course (Currie 2011; Torche and Nobles 2024). Some evidence on prenatal heat exposure in cooler climates aligns with this (Brink et al. 2024). However, this thesis points to the important role of in-utero selection (Bruckner and Catalano 2018; Hajdu 2025). My findings suggest that in some contexts, prenatal heat exposure may instead lead to a positively selected cohort with better outcomes at and after birth – particularly for low SES groups. This means that disadvantages experienced postnatally in response to temperature and other shocks could be underestimated for low SES groups. Hence, the role of early life temperature exposure in shaping social stratification deserves further empirical attention and its conceptualization may be revisited based on new evidence.

5 Conclusion

Extreme heat poses an increasing and serious threat to the health and well-being of pregnant mothers and infants and understanding these impacts and their consequences for population composition is urgent. This thesis has extended the literature on climate impacts on populations by addressing several theoretical gaps and methodological inconsistencies in existing scholarship. The findings underline that extreme heat may impact maternal health, infant health, and population composition, particularly in vulnerable LMICs that are both disproportionately affected by climate change and have lower levels of maternal and infant health. Extreme heat shapes the health of pregnant individuals and infants through both biological and health-related behavioural mechanisms. These include changes in antenatal care access, male-biased pregnancy loss, induced sex-selective abortion in son preference contexts, and intensified prenatal selection. However, the effect of extreme heat on maternal and infant health is specific to geographic, socio-cultural, and institutional contexts, as are the relevant temperature thresholds, and underlying mechanisms. Additionally, the findings underline that even when biological health mechanisms are at play, their social embedding needs to be considered. My work shows that the impacts of extreme heat are socially stratified and that extreme heat has the potential to widen gaps in maternal and infant health, both globally and within populations. In a warming climate that poses serious threats to population health, improving and protecting maternal and infant health must remain a global priority. Although country settings can be highly heterogeneous along many dimensions, this thesis presented a comprehensive methodological framework for the study of temperature impacts on births, which can be applied to investigate a range of outcomes in diverse contexts. Further research on the impacts of extreme heat in the most vulnerable populations is urgently needed to develop targeted interventions that safeguard the health of pregnant mothers and infants. Given the sensitivity of the gestational and prenatal period, these interventions may potentially benefit individuals throughout their life-courses.

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