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The Costs of Climate Change: The Effect of Rising Temperatures on Children's Nutritional Status in India

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The Generative AI tool ChatGPT was used to assist in coding and data analysis. Appendix 8.4 of this thesis provides a detailed account of the use of the Generative AI tool during the development of this thesis. By submitting this thesis I declare that I am fully responsible for the accuracy and completeness of its content.

Abstract

This thesis investigated whether rising temperatures affect children's nutritional status in India negatively, in order to examine whether the increasing temperatures (Mourougan et al., 2024) and the prevalence of child malnutrition (Das et al., 2021; Tripathi et al., 2023) in this developing country are related. Existing literature indicates that increasing temperatures influence (children's) health and nutritional status negatively through multiple channels (e.g. Bharambe et al., 2023; Biswas et al., 2024; Ebi & Paulson, 2007; Motarjemi et al., 1993). Nutritional status is measured by weight-for-age Z scores (WAZ), which is also used to examine how rising temperatures affect the probability of children being underweight (WAZ <-2). WAZ and other health-related data from NFHS-4 and NFHS-5 are combined with weather data (e.g. daily temperatures) from ERA5, and create a district-wave panel with 467 districts in total across the two waves. A binned temperature approach is utilized, where bin 4 (24-28°C) is used as the reference group, and heterogeneity analyses are performed as well. However, the findings do not align with expectations based on existing literature. Therefore, the null hypothesis, which states that rising temperatures negatively affect children's nutritional status in India, cannot be rejected.

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1 Introduction

The temperatures are rising globally (Goshua et al., 2021). Due to climate change and the increasing temperatures, droughts (Algur et al., 2021) and heatwaves (Mourougan et al., 2024) will occur more frequently and intensely in the future (Abramopoulos et al., 1988; Ebi & Paulson, 2007). The rising temperatures, droughts and extreme temperatures lead to a decline in human health (Deschenes, 2014; Goshua et al., 2021) through several pathways (Bharambe et al., 2023; Ebi & Paulson, 2007; Motarjemi et al., 1993; Xu et al., 2012).

Children are more vulnerable and sensitive to high temperatures than adults (Algur et al., 2021; Ebi & Paulson, 2007; Xu et al., 2012). Baker and Anttila-Hughes (2020) found a strong negative relation between temperature and child weight in Sub-Saharan Africa, indicating that rising temperatures affect children's health. Moreover, children's health impacts long-term outcomes. Children who suffer from poor health tend to have a lower social status, worse health and lower educational achievement in their adulthood (Case et al., 2005). In order to achieve Zero Hunger and Good Health and Well-Being – the second and third Sustainable Development Goals (SDGs) – globally by 2030, Goal 13: Climate Action – Take urgent action to combat climate change and its impact, needs to be realized (Aromolaran et al., 2024; Climate ADAPT, n.d.; United Nations, n.d.; United Nations Global Compact, n.d.). However, the period from 2010 till 2019 was the hottest decade measured (United Nations, n.d.). Developing countries are more vulnerable to climate change effects than developed countries due to economic, environmental and social conditions (Nanda & UN.ESCAP, 2009).

This thesis investigates the influence of rising temperatures on children's[1] health in India in terms of their nutritional status, measured by weight-for-age Z scores (WAZ) and the probability of being underweight, in order to examine whether the increasing temperatures (Mourougan et al., 2024) and the prevalence of child malnutrition (Das et al., 2021; Tripathi et al., 2023) in this developing country are related.

According to previous research (Algur et al., 2021; Burgess et al., 2017; Mourougan et al., 2024), some of the consequences of the temperature increases have shown to affect health and

[1] Children are defined as children under 5 years old / 0-59 months.

nutrition of Indian children in a negative way, and to increase mortality and morbidity rates in the developing country. Rahut et al. (2024) found that rising temperature is a significant determinant of child malnutrition in India.

Malnutrition is an important child health issue (Das et al., 2021). Comparing National Family Health Surveys from the years 2015-2016 with 2019-2021 shows that the nutritional status and health of Indian children has improved. However, the 2019-2021 survey still measured a wasting rate of 19%, a stunting rate of 36%, and an underweight rate of 32% across all Indian districts included in these surveys (Tripathi et al., 2023). A paper that looked specifically at the Indian state West Bengal using these surveys found that it varied by district whether the percentage of underweight children under five decreased or increased (Das et al., 2021). Furthermore, Rais and Asif (2024) state that regional differences exist in the impact of climate change (including rising temperatures) on health in India.

Prior studies found that increasing temperatures influence (children's) health and nutritional status negatively through multiple channels. For example, high temperatures have an effect on nutrition through diseases, such as water- and foodborne illnesses. This increases the likelihood of diarrhoeal diseases, which affect children's nutritional status negatively (Carlton et al., 2016; Ebi & Paulson, 2007; Gorospe & Oxentenko, 2012). In addition, increasing temperatures and droughts influence agriculture, income and productivity, which negatively affect nutritional status (Algur et al., 2021; Bharambe et al., 2023; Burgess et al., 2017; Rais & Asif, 2024). Other channels are contaminated food and contaminated water, which can also contribute to the spread of illnesses and worsen nutritional status (Biswas et al., 2024; Ebi & Paulson, 2007; McMichael et al., 2006; Motarjemi et al., 1993).

Furthermore, a lot of previous research shows that increasing temperatures lead to (infant) mortality (e.g. Burgess et al., 2014; Geruso & Spears, 2018). In contrast, this thesis investigates the effect of rising temperatures on children's health in India, in terms of their nutritional status measured by weight-for-age Z scores (WAZ). Additionally, these WAZ scores are used to examine how rising temperatures affect the probability of children being underweight.[2] To analyse this,

[2] Underweight is defined as having a weight-for-age Z score below -2; this is based on the World Health Organization (WHO) growth standards (International Institute for Population Sciences (IIPS) and ICF, 2022; Ministry of Health & Family Welfare, 2021). For a more detailed explanation see section 3.2.

district-level data on children's health (i.e. WAZ scores) from the two most recent waves of the National Family Health Survey (i.e. NFHS-4 and NFHS-5) are used in combination with weather data (i.e. daily temperatures, precipitation, relative humidity, wind speed and wind direction) from Copernicus European ReAnalysis (ERA5) (Copernicus Climate Data Store, n.d.-a, n.d.-b; Ministry of Health & Family Welfare, n.d.). A binned temperature approach is utilized, which makes it possible to combine the wave-level aggregated health data with the high frequency weather data (i.e. daily temperatures) to create a district-wave panel. The binned temperature approach groups the daily average temperatures of all the Indian districts in the sample into several bins with one bin as a reference group (Burgess et al., 2011, 2017; P. Zhang et al., 2018). In contrast to this approach, several previous studies do look at the effect on nutritional status measured by WAZ scores, but not at rising temperatures as main determinant (e.g. Rajan et al., 2024), and/or do not use a binned temperature approach (e.g. Rahut et al., 2024). Moreover, papers often use NFHS-4 or NFHS-5 rather than both (e.g. Biswas et al., 2024; Mahapatra et al., 2021; Rahut et al., 2024), or use the less recent data from India Human Development Survey (IHDS) (e.g. Mandal & Sarma, 2020; Sedova et al., 2020). Additionally, research that uses a binned temperature approach often looks outside of India (e.g. Baker & Anttila-Hughes, 2020) and/or other outcome variables as opposed to nutritional status measured by WAZ scores/probability of being underweight (e.g. Burgess et al., 2011). However, the binned temperature approach has not been used in combination with this recent district-level data of health and daily temperatures (i.e. NFHS-4, NFHS-5 and ERA5) to investigate the effect of rising temperatures specifically on children's nutritional status in India measured by WAZ scores. Therefore, this thesis contributes to the existing literature. Furthermore, the district-level analysis provides more detailed information compared to a national- or subnational-level analysis.

Therefore, this study will answer the following research question: *What is the effect of rising temperatures on the nutritional status of children under five in India?*

Given the rising temperatures in India (Mourougan et al., 2024), child malnutrition being a public health issue in the country (Rajan et al., 2024), children's health influencing long-term outcomes (Case et al., 2005), and undernutrition being a main cause of infant mortality in developing countries (Nandy et al., 2005), this thesis is relevant for societal contribution by investigating whether rising temperatures in India are associated with children's nutritional status and their probability of being underweight. This information is useful for policymakers to assess whether fighting increasing temperatures contributes to tackling the child malnutrition problem in India. Additionally, the findings of this thesis help in achieving the second (i.e. Zero Hunger) and third (i.e. Good Health and Well-Being) SDGs (Aromolaran et al., 2024; Climate ADAPT, n.d.; United Nations Global Compact, n.d.).

This thesis is structured as follows. In chapter 2 the literature review is discussed and the hypotheses are formulated. Chapter 3 describes the data and methodology followed by the analysis and results in chapter 4. Chapter 5 provides a discussion, limitations of the paper, and recommendations for future research, while chapter 6 presents the conclusion. Furthermore, chapter 7 provides a list of references and chapter 8 contains the appendices.

2 Literature Review

The temperatures in India are increasing every year (Mourougan et al., 2024). This developing country (Dhara et al., 2013) is faced with droughts created during extreme dry and hot periods (Bharambe et al., 2023), and heatwaves (Mourougan et al., 2024). Extreme temperatures in India raise mortality and morbidity rates (Burgess et al., 2017; Mourougan et al., 2024). Droughts happen every year in several areas of the country and affect health and nutrition of children negatively (Algur et al., 2021). Simultaneously, the percentage of Indian children with undernutrition has been high in the last few decades (Corsi et al., 2016). Even though it has improved lately, an underweight rate of 32% was measured among children in the 2019-2021 NFHS (Tripathi et al., 2023). Rahut et al. (2024) found that rising temperature is a significant determinant of child malnutrition in India since it affects food production negatively. According to Rais & Asif (2024), the effect of climate change (including rising temperatures) on health varies across regions in India.

Children are more vulnerable and sensitive to high temperatures than adults for several reasons. Children need more time to adjust to higher temperatures than adults (Ahdoot et al., 2024). Furthermore, they depend on caretakers to protect them, they have a higher exposure to contaminated food and water per unit of body weight, and their organ systems are not completely developed yet (Ahdoot et al., 2024; Ebi & Paulson, 2007; Xu et al., 2012). Children also have a higher exposure to heat and higher risk for vector borne-related illnesses because they spend more time outside compared to adults, and are more likely to suffer from allergic and infectious illnesses as a consequence of high temperatures (Ebi & Paulson, 2007; Xu et al., 2012).

The sections below explain how rising temperatures influence children's nutritional status through multiple pathways. Figure 2.1.1 shows a conceptual framework in order to visualize this relation.

2.1 Channels

2.1.1 Agriculture, Income and Productivity

Increasing temperatures increase the number of droughts and their intensity (Bharambe et al., 2023). They impact food security and the health and nutritional status of children negatively since droughts reduce water availability needed for agriculture and decrease the production (both quality and quantity) of food, raising the chances of diseases and malnutrition (Algur et al., 2021; Bharambe et al., 2023; Rais & Asif, 2024). In addition, the income of people working in the agricultural sector and agricultural productivity can decrease due to high temperatures, which contributes to mortality in rural India; people in rural India mostly rely on subsistence agriculture (Algur et al., 2021; Burgess et al., 2017; Rais & Asif, 2024). Somanathan et al. (2021) state that high temperatures also lead to a decline in worker productivity and more workers being absent. For some workers this results in lower wages, which can lead to nutritional deficiencies and therefore underweight, as less money is available for food (Algur et al., 2021; Somanathan et al., 2021).

2.1.2 Diseases

Furthermore, extreme hot temperatures affect allergic (e.g. eczema) and infectious diseases (e.g. malaria and gastrointestinal diseases), which can lead to undernutrition (Gorospe & Oxentenko, 2012; Xu et al., 2012). Mosquitoes and the pathogens they can transmit are influenced by rising temperatures (Ahdoot et al., 2024). In addition, the possibility of disease transmissions and the period in which parasites and vectors live is influenced by temperature. Higher temperatures increase the likelihood of diarrhoeal diseases since some water- and foodborne diseases react to climate (Carlton et al., 2016; Ebi & Paulson, 2007). Moreover, diarrhoeal illnesses are one of the main causes of infant mortality and affect children's growth negatively by causing nutritional deficits (Carlton et al., 2016; Motarjemi et al., 1993). Caulfield et al. (2004) found that children with diseases, such as diarrhoea and malaria, have a higher relative risk of dying due to low weight-for-age.

2.1.3 Contaminated Food and Water

Another channel is contaminated food, which can also contribute to the spread of diseases, especially diarrhoea-related ones, and malnutrition (Motarjemi et al., 1993). Some food-borne illnesses respond to climate (Ebi & Paulson, 2007). It was found that storing weaning food at high temperatures and the severity of contamination are linked to each other (Motarjemi et al., 1993). Food poisoning, such as salmonellosis, is related to temperature (Ebi & Paulson, 2007). Cholera bacteria and salmonella multiply themselves faster when temperatures are high (McMichael et al., 2006). The paper of Kovats et al. (2004) about European countries also states that there is a relation between the quantity of salmonella cases and temperature. Children are vulnerable to food-borne illnesses. Their odds of getting intoxicated or infected resulting in illnesses are high when eating contaminated food (Motarjemi et al., 1993).

Contaminated water can also affect nutritional status. High temperatures are associated with poorer groundwater quality, which in turn is related to an increased risk of underweight (Biswas et al., 2024). Moreover, contaminated water sources are related to diarrhoeal illnesses (Motarjemi et al., 1993).

This leads to the following hypothesis:

(H_1): "*Rising temperatures have a negative effect on the nutritional status of children under five in India.*"

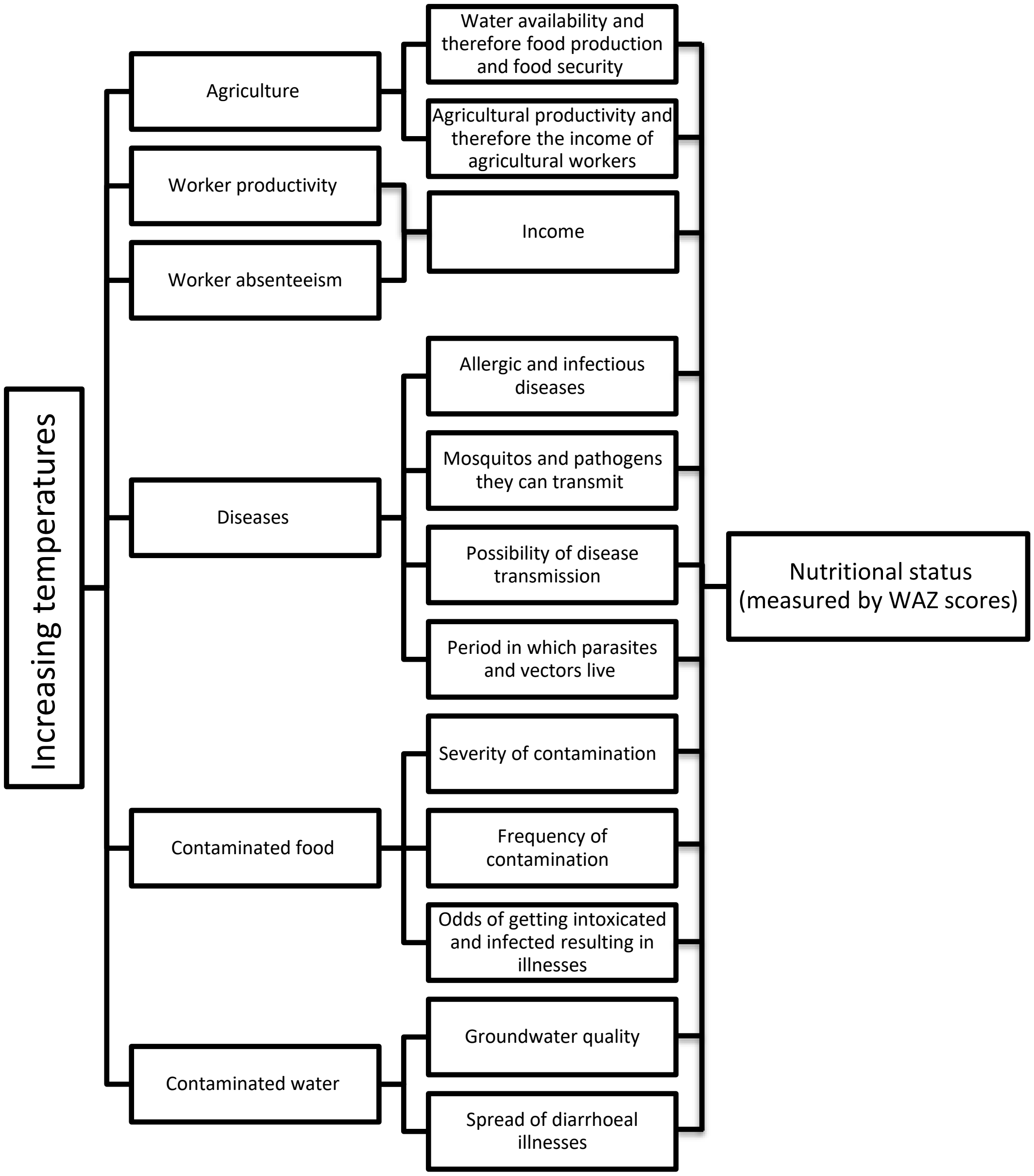

FIGURE 2.1.1: CONCEPTUAL FRAMEWORK OF THE RELATIONSHIP BETWEEN INCREASING TEMPERATURES AND CHILDREN'S NUTRITIONAL STATUS

2.2 Heterogeneity Effects

Previous literature suggests that the effect of temperature on nutritional status may vary between poor versus non-poor people, living in rural versus urban areas, and between males versus females. Biswas et al. (2024) state that high temperatures are related to poorer groundwater quality, while income influences the accessibility of clean water, resulting in child undernutrition differences between poor and non-poor people. Moreover, Sedova et al. (2020)

found that people with a low income in rural India react more intensely to changes in temperature than people with a high income living in the same areas.

The effect of temperature on nutritional status may vary across urban and rural because 75% of the people in urban India work in non-agriculture sectors, while rural India is mainly agriculture-dependent (Burgess et al., 2017; Rais & Asif, 2024). In addition, people living in rural India are more seriously affected by heat-related diseases (Mourougan et al., 2024). The paper from Burgess et al. (2017) found that high temperatures rise the mortality rate in rural, but not in urban India. Furthermore, both NFHS-4 and NFHS-5 show a higher percentage of Indian children being underweight in rural than in urban areas (Ministry of Health & Family Welfare, 2021; Ministry of Health and Family Welfare, 2016).

In India, daughters typically receive less care and attention because sons are preferred in the country. In a lot of households, sons/males receive more resources than daughters/females (Mitra, 2014). Females face discrimination in terms of health, as the health of males is prioritized within a lot of households (Mondal & Dubey, 2020; Tirkey, 2022). Expenditure for hospitalization is lower for females than males (Kastor & Mohanty, 2018; Mondal & Dubey, 2020). Additionally, mothers prefer to breastfeed their sons over their daughters (Algur et al., 2021). Breastmilk not only contains lots of nutrition, but also reduces exposure to contaminated water and food that can cause diseases (Motarjemi et al., 1993). Households also tend to invest less in females' nutrition, which makes females more vulnerable during droughts (Algur et al., 2021).

This makes it interesting to examine whether the impact of rising temperatures on child nutritional status varies between poor versus non-poor people, rural versus urban areas, and males versus females. Therefore, the following hypotheses are formulated:

(H_2): "*The effect of rising temperatures on the nutritional status of children under five in India is more negative for poor people than for non-poor people.*"

(H_3): "*The effect of rising temperatures on the nutritional status of children under five in India is more negative for people living in rural areas than in urban areas.*"

(H_4): "*The effect of rising temperatures on the nutritional status of children under five in India is more negative for females than for males.*"

3 Data and Methodology

3.1 Health Data

The health data (i.e. WAZ scores) used for this research is obtained from the two most recent waves of the National Family Health Survey (NFHS) in India: NFHS-4, 2015-2016 and NFHS-5, 2019-2021. They are the only NFHS waves that provide indicators measured at the district level (Ministry of Health & Family Welfare, n.d.). These comprehensive surveys performed under the supervision of the Ministry of Health and Family Welfare collect data on health, nutrition and the population from a representative sample of Indian households (Asharaf & Tol, 2024; deSouza et al., 2022; Ministry of Health & Family Welfare, n.d.; Rajan et al., 2024). In total, approximately 707 districts, 29 states, 7 union territories and 600,000 households are covered in each wave (Asharaf & Tol, 2024; Ministry of Health & Family Welfare, n.d.; Tripathi et al., 2023). For this thesis, the data from the two waves (i.e. wave 1 = NFHS-4; wave 2 = NFHS-5) are aggregated at the district level[3] and merged using the variables included in the surveys that identify the state and district. Since the surveys were conducted in two phases, not every district was surveyed every year within each wave. Therefore, a district-wave panel is created with a total of 934 observations from 467 districts in 29 states across two waves after merging NFHS-4, NFHS-5 and the weather data. The working paper of Rajan et al. (2024) along with other recent papers (Biswas et al., 2024; Mahapatra et al., 2021) also use NFHS data to analyse child nutritional status in India. However, they solely use one wave of NFHS, do not use a binned temperature approach, and/or do not look at rising temperature as main determinant of child nutritional status.[4]

[3] The data from the two waves are aggregated at the district level because the households surveyed in wave 1 and wave 2 are not the same.

[4] Panel data from India Human Development Survey (IHDS) utilized by other literature (Mandal & Sarma, 2020; Sedova et al., 2020) that studies the impact of weather has also been considered. However, since this survey was conducted in 2005-2006 and 2011-2012, it was decided to utilize NFHS due to its recency (University of Maryland, n.d.).

3.2 Dependent Variable

The nutritional status of children under five is measured by weight-for-age Z scores (WAZ), i.e. the dependent variable. This is a continuous variable that can range from WAZ scores of -6 to 6, and indicates how many standard deviations (SD) a child's weight deviates from the median weight of a reference population with the same age and sex.[5] Analyses are also performed with a binary dependent variable called $Underweight$ to examine how increasing temperatures affect the probability of children being underweight.[6] Based on World Health Organization (WHO) growth standards, children having a WAZ score lower than minus two standard deviations (-2 SD) from the reference population's median are defined as underweight, children having a WAZ score lower than minus three standard deviations (-3 SD) are defined as severely underweight (International Institute for Population Sciences (IIPS) and ICF, 2022; Ministry of Health & Family Welfare, 2021). Since the data is aggregated at the district level, the binary dependent variable having a value of 1 indicates that the average WAZ score for children in the district is classified as underweight (i.e. WAZ <-2 SD), and a value of 0 means that the average WAZ score for children in the district is classified as not underweight (i.e. WAZ >-2 SD). A robustness check with severely underweight (i.e. WAZ <-3 SD) was considered, however, it is not able to perform since no district is severely underweight. In the sample of 934 observations from 467 districts across the two waves, WAZ scores range from -2.67 to -0.22, see Figure 8.1.1. In total, 41 districts have average WAZ scores classified as underweight (29 districts in wave 1 and 12 districts in wave 2), while no district is classified as severely underweight, see Table 8.1.1. Other studies have used WAZ scores and this definition of underweight to examine the effect of temperature on child nutritional status in various locations (Baker & Anttila-Hughes, 2020; Mahapatra et al., 2021; Rahut et al., 2024). This measure has also been used by studies analysing nutritional status of Indian children where temperature was not the main independent variable (Biswas et al., 2024; Rajan et al., 2024).

[5] The WAZ scores are calculated based on the LMS method using the following formula: $z = \frac{\left(\frac{y}{M(t)}\right)^{L(t)} - 1}{S(t)L(t)}$, where y = child's weight and $M(t)$ = reference median weight at age t (Cole & Green, 1992). The values of the parameters (i.e. L, M, S) are stated in the WHO growth standards tables (World Health Organization, n.d.).

[6] Measuring nutritional status as a binary variable of underweight is similar to the paper of Biswas et al. (2024).

3.3 WAZ-Related Controls

Following previous literature, several variables obtained from NFHS are included in the models as controls. Households possession of a refrigerator and the household's source of drinking water are used as controls because storing weaning food in hot temperatures and contaminated water sources affect nutritional status negatively through contamination, infections and diseases that can lead to weight loss (Biswas et al., 2024; Motarjemi et al., 1993). Maternal education leads to higher WAZ values because it increases the health knowledge and leads to better health-related practices (Biswas et al., 2024; Corsi et al., 2016; Glewwe, 1999; Rajan et al., 2024; Smith et al., 2003). Therefore, it is also incorporated in the analyses as a control. Child age is included as a control as well, as in the paper by Rajan et al. (2024).[7] The variables wealth index,[8] urban and sex used for the heterogeneity analyses were also obtained from NFHS. See Table 3.7.1 Table 3.7.1for the definitions of the (control) variables and Table 8.1.1 for the summary statistics.

3.4 Temperature Data

Publicly available satellite-based data from Copernicus European ReAnalysis (ERA5) are used in order to create daily average temperatures in degrees Celsius at the district level, i.e. the variable of interest. The daily average temperatures are constructed from ERA5 hourly temperature data in order to utilize a binned temperature approach, see section 3.6. The data represent global gridded datasets at a 0.25° x 0.25° spatial resolution, which is 25 x 25 km at the equator (Copernicus Climate Data Store, n.d.-a; Global Data Lab, n.d.). ERA5 reanalysis data are widely used and recognized due to its detailed spatial and temporal resolutions and high quality (Global Data Lab, n.d.; Liu et al., 2021; Sedova et al., 2020). For example, ERA5 data (including temperature) have been used by Sedova et al. (2020) to examine the distributional effects of weather variance in rural India.

[7] Mobile phone ownership by the mother was considered to utilize as a control since this has proved to be related to higher WAZ scores and reduced likelihood of a child being underweight, for example, due to increased access to health information (De & Pradhan, 2023; Rajan et al., 2024). However, due to the low number of observations for this control, it is not included in the models.

[8] Biswas et al. (2024) also used the variable wealth index to distinguish between poor and wealthy households.

3.5 Weather Controls

Additionally, ERA5 daily average data on relative humidity, wind speed and wind direction, as well as daily precipitation data[9], are used to aggregate the data of these variables at the district and wave level (Copernicus Climate Data Store, n.d.-b). These serve as weather controls (W) as suggested by previous literature that study temperature effects, to take into account concurrent variations of temperature and other weather variables (Burgess et al., 2017; Chen & Yang, 2019; Graff Zivin et al., 2020; Yu et al., 2019; P. Zhang et al., 2018). Moreover, Rahut et al. (2024) state that rainfall is negatively related to child underweight in India. However, it is positively related to child underweight in Timor-Leste and Bangladesh; probably due to increases in the distribution of diseases and crop failure (Rahut et al., 2024). In addition, previous literature (Carlton et al., 2016; Caulfield et al., 2004; Ebi & Paulson, 2007) states that the possibility of disease transmissions is influenced by precipitation and therefore influences health negatively. Humidity affects human health negatively by influencing distribution patterns of infectious diseases (Mucci et al., 2023; G. Zhang et al., 2023). See Table 3.7.1 for the definitions of the weather controls and Table 8.1.1 for the summary statistics.

3.6 Binned Temperature Analysis

The binned temperature approach is used in order to investigate the effect of rising temperatures on children's nutritional status in India. This empirical strategy has been used by previous literature (Burgess et al., 2017; Chen & Yang, 2019; Li et al., 2021; Yu et al., 2019; P. Zhang et al., 2018), and enables combining the high frequency weather data (i.e. daily temperatures) with the wave-level aggregated health data from NFHS-4 and NFHS-5 (P. Zhang et al., 2018). See Figure 3.6.1 for the distribution of the daily average temperatures in the 467 districts for the years in the two waves (i.e. 2015-2016 and 2019-2021), with a peak at approximately 27°C. The binned temperature approach groups the daily average temperatures measured in degrees Celsius of all the 467 Indian districts in the sample into six bins (n) with a

[9] Daily precipitation is not an average, but the total sum of precipitation throughout the day, because precipitation can accumulate and be stored (e.g. in the soil) in contrast to the other weather variables (Burgess et al., 2017).

width of 4°C each, see Figure 3.6.2. The height of the bars reflects the number of days averaged across the 467 districts and waves[10] with daily average temperatures that fall within one of the six bins. In order to avoid collinearity, temperature bin 4 (24-28°C) is omitted and used as the reference category since its bar is the highest, i.e. the most common temperatures observed in the 467 districts are between 24-28°C. Bin 3 (20-24°C) and bin 6 (≥32°C) are utilized as alternative omitted bins as robustness checks in section 4.3, because bin 3 has the most optimal weather temperature for humans and bin 6 has the highest temperature (Asseng et al., 2021).

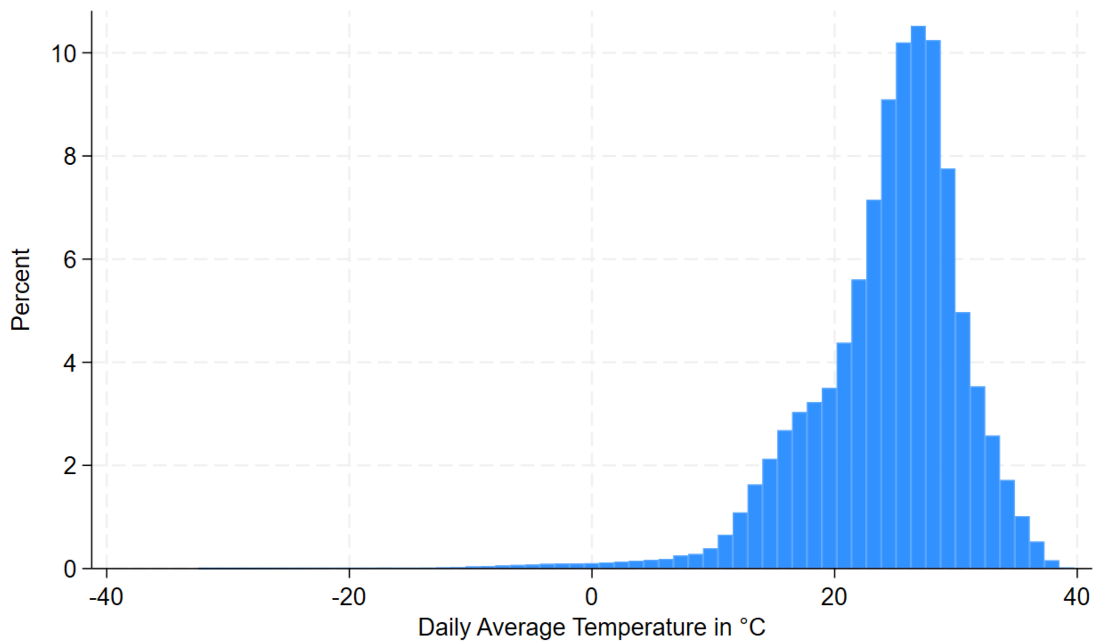

FIGURE 3.6.1: DISTRIBUTION OF DAILY AVERAGE TEMPERATURES

Notes: The distribution of the daily average temperatures in the 467 districts for the years in the two waves (i.e. 2015-2016 and 2019-2021).

[10] In order to create a district-wave panel, the mean of the average number of days from the years 2015-2016 is used as the average number of days in wave 1, and the same approach is used for the years 2019-2021 in wave 2, because not every district was surveyed every year within each wave, as already explained in section 3.1.

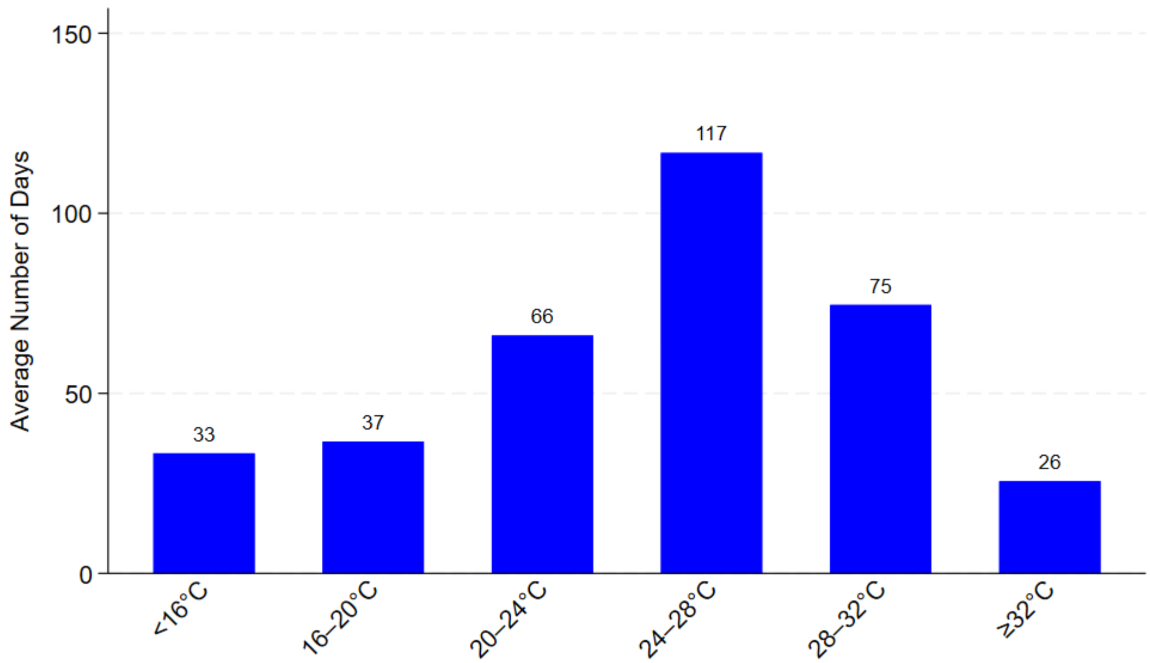

FIGURE 3.6.2: AVERAGE NUMBER OF DAYS IN EACH TEMPERATURE BIN

Notes: The height of the bars reflects the number of days averaged across the 467 districts and waves with a daily average temperature that falls within one of the six bins.

3.7 Regression Models

Both fixed effects linear regression models and fixed effects Linear Probability Models (LPM) are employed in order to perform analyses with the continuous variable WAZ and the binary variable $Underweight$.[11] This leads to the following two regression equations:

(1)
$$WAZ_{d,t} = \sum_{n} \beta^n T_{d,t}^n + \sigma W_{d,t} + \lambda C_{d,t} + \alpha_d + \gamma_t + \epsilon_{d,t}$$

(2)
$$Underweight_{d,t} = \sum_{n} \beta^n T_{d,t}^n + \sigma W_{d,t} + \lambda C_{d,t} + \alpha_d + \gamma_t + \epsilon_{d,t}$$

The variables from NFHS-4 and NFHS-5 represent the average values for children or households (depending on the type of variable) within district d in wave t, since the panel is at the district-

[11] The LPM treats the binary variable as a continuous variable and estimates the probability of being underweight.

wave level. The weather variables also represent averages within district d in wave t, except for precipitation which is the sum of daily precipitation values within district d in wave t.[12] The two regression equations are identical except for the dependent variables. $WAZ_{d,t}$ denotes the weight-for-age Z scores in wave t for district d. $Underweight_{d,t}$ has a value of 1 if district d in wave t is classified as underweight (i.e. WAZ <-2 SD), and 0 if not classified as underweight (i.e. WAZ >-2 SD). $T^{n}_{d,t}$ represents the number of days in wave t and district d with daily average temperatures that fall into bin n ($n = 1,2, \dots ,6$). Therefore, $T^{1}_{d,t}$ is the number of days in wave t and district d with daily average temperatures below 16°C, and $T^{6}_{d,t}$ the number of days with daily average temperatures above 32°C. β^{n} is the main coefficient, it indicates the marginal effect on WAZ scores (in equation 1) and the probability of being underweight (i.e. WAZ <-2 SD) (in equation 2) of another day with temperature in bin n compared to a day with temperature in the reference bin 4 (24-28°C). This means that a negative/positive β^{n} does not necessarily mean that the absolute effect on WAZ scores is negative/positive, but relative to the omitted bin 4 (24-28°C) the effect on WAZ scores is negative/positive. $W_{d,t}$ captures the weather controls and $C_{d,t}$ the WAZ-related controls. α_{d} denotes district fixed effects to control for unobserved and time-invariant effects of district characteristics. γ_{t} denotes wave fixed effects, which control for unobserved factors common across the waves, and standard errors ($\epsilon_{d,t}$) are clustered at the district level to account for within-district serial correlation.

Some controls are dummy variables and some are categorical variables transformed into (a set of) dummy variables. Since the data is aggregated at the district-wave level, each of these dummy variables represent the share of observations with a value of 1 within district d in wave t. See Table 3.7.1 for a definition of each variable. As mentioned in section 2.2, previous literature suggests the impact of rising temperature on children's nutritional status in India varies between poor versus non-poor people, living in rural versus urban areas, and between males versus females. Therefore, these heterogeneity effects are analysed as well using the dummy variables wealth index, urban and sex, see Table 3.7.1 for the definitions of the variables and Table 8.1.1 for the summary statistics. To check for multicollinearity, a Variance Inflation Vector (VIF) test and

[12] Precipitation is not the average, but the sum value of daily precipitation within district d in wave t, because precipitation can accumulate and be stored (e.g. in the soil) in contrast to the other weather variables (Burgess et al., 2017).

a correlation matrix of the variables are performed and show low to moderate correlations, see Table 8.2.1. Solely the control relative humidity shows to be highly correlated to temperature bin 6 (≥32°C). However, existing literature (Chen & Yang, 2019; Yu et al., 2019; P. Zhang et al., 2018) states that this high correlation is logical and that it is important to include this weather control in the models. As a robustness check, the regression models are also performed without the weather control relative humidity, see section 4.3.

TABLE 3.7.1: LIST OF VARIABLES

Type of Variable	Variable name	Definition
Dependent	WAZ	Weight-for-age Z score
Dependent	Underweight	Dummy variable: 1 = underweight; 0 = not underweight
Independent	Temperature Bin 1 - 6	Number of days with daily average temperatures that fall within one of the six bins
Weather Control	Precipitation	Precipitation in centimetres
Weather Control	Relative Humidity	Relative humidity in percentages
Weather Control	Wind Speed	Direction wind is coming from in degrees
Weather Control	Wind Direction	Wind speed in M/S
WAZ-Related Control	Child Age	Age of child in months
WAZ-Related Control	Refrigerator	Household possesses a refrigerator (Dummy variable: 1 = yes; 0 = no)
WAZ-Related Control	Source of Drinking Water	Major source of drinking water (Categorical variable transformed into a dummy variable: 1 = improved; 0 = unimproved)
WAZ-Related Control	Maternal Education	Mother's highest educational level (Categorical variable transformed into three dummy variables: 1 = primary, secondary or higher; 0 = no education)
Heterogeneity Analysis	Wealth Index	Measure of a household's living standard (Categorical variable transformed into a dummy: 1 = non-poor; 0 = poor)
Heterogeneity Analysis	Urban	Type of place of residence (Dummy variable: 1 = urban; 0 = rural)
Heterogeneity Analysis	Sex	Sex of child (Dummy variable: 1 = male; 0 = female)

Notes: The variables represent the average values within district d in wave t, except for precipitation which is the sum of daily average precipitation values, since the panel is at the district-wave level. The dummy variables used as controls represent the share of observations with a value of 1 within district d in wave t. The categorical variable Source of Drinking Water is transformed into a dummy variable according to the Demographic and Health Surveys guide: 1 = improved (i.e. piped into dwelling, piped to yard/plot, public tap/standpipe, tube well or borehole, protected well/spring, rainwater, tanker truck, cart with small tank, bottled water); 0 = unimproved (i.e. unprotected well/spring, river/dam/lake/ponds/stream/canal/irrigation channel, other) (DHS Program, n.d.). Due to the low number of observations in the extreme categories, Wealth Index is transformed into a dummy variable: 1 = non-poor (i.e. top 50%); 0 = poor (i.e. bottom 50%).

4 Analyses and Results

4.1 Main Results

The fixed effects linear regression is estimated with and without control variables in order to estimate the relationship between children's WAZ and increasing temperatures using a binned temperature analysis, see Table 4.1.1. In model 1 without controls, bin 1 (<16°C) and bin 6 (≥32°C) show statistically significant results at the one percent level. The first bin has a coefficient of 0.0096. This indicates that an extra day with a temperature in bin 1 (<16°C) increases the WAZ score by 0.0096 SD (i.e. better nutritional status) compared to a day in the omitted bin, which is bin 4 (24-28°C). The last bin has a coefficient of -0.0052, meaning that an additional day with a temperature in bin 6 (≥32°C) decreases the WAZ score by 0.0052 SD (i.e. worse nutritional status) compared to a day in the omitted bin. In value terms, the average WAZ is -1.534258 for males of 30 months in wave 1[13], which means that an additional day with a temperature in bin 1 (<16°C), compared to a day with a temperature in omitted bin 4 (24-28°C), increases the weight of 30-month-old males from 11.109 kg to 11.121 kg, i.e. increases by 12 grams which corresponds to an increase of 0.11%.[14] An additional day with a temperature in bin 6 (≥32°C) decreases the weight of 30-month-old males by 7 grams, from 11.109 kg to 11.102 kg (-0.06%). However, the other bins are not statistically significant in model 1.

Including both weather and WAZ-related controls (model 2) change the signs of the bins' coefficients, except for bin 1 (<16°C) which stays positive. However, solely bin 3 (20-24°C) shows to be statistically significant in this model. The coefficient of -0.0028 means that an additional day with a temperature in bin 3 (20-24°C) decreases the WAZ score by 0.0028 SD (i.e. worse nutritional status) compared to a day in the omitted bin, which is bin 4 (24-28°C). In value terms, an additional day with a temperature in bin 3 (20-24°C) decreases the weight of 30-month-old

[13] The value term was checked for males of 30 months, because there are more males in the sample than females and the average age for males (in wave 1) is approximately 30 months, see Table 8.1.1.

[14] As explained in section 3.2, this is calculated based on the LMS method using the following formula: $z = \frac{\left(\frac{y}{M(t)}\right)^{L(t)} - 1}{S(t)L(t)}$, where y = child's weight and $M(t)$ = reference median weight at age t (Cole & Green, 1992). The values of the parameters (i.e. L, M, S) are stated in the WHO growth standards tables (World Health Organization, n.d.).

males by 4 grams, from 11.109 kg to 11.105 kg (-0.04%). Furthermore, model 3 only includes the weather controls, while model 4 only includes the WAZ-related controls. Both models only show a statistically significant result for the first temperature bin 1 (<16°C), which is positive in both models. The weather control relative humidity, along with the WAZ-related controls maternal education primary and maternal education secondary show statistically significant positive coefficients. This indicates that WAZ scores increase (i.e. better nutritional status) when relative humidity and the share of mothers with primary and secondary education as their highest educational level increase. The weather control precipitation and WAZ-related control child age show negative statistical significance, suggesting WAZ scores decrease when precipitation and child age increase. The R-squared value is relatively high without including controls, indicating a good model fit. However, including controls raises the R-squared values even more, implying that they add explanatory value.

Additionally, the fixed effects Linear Probability Model is estimated with and without control variables with the use of a binned temperature analysis to examine how rising temperatures affect the probability of children being underweight (i.e. WAZ <-2 SD), see Table 4.1.2. Without adding controls (model 1), statistically significant results are found for bin 2 (16-20°C) at the five percent level and for bin 6 (≥32°C) at the one percent level. The second bin has a coefficient of -0.0051. This indicates that an extra day with a temperature in bin 2 (16-20°C) decreases the probability of children being underweight by 0.0051 compared to a day in omitted bin 4 (24-28°C). The sixth bin has a coefficient of 0.0071, implying that an additional day with a temperature in bin 6 (≥32°C) increases the probability of children being underweight by 0.0071 compared to a day in the omitted bin. The other temperature bins are not statistically significant in the first model.

Once both weather and WAZ-related controls are included (model 2), the coefficients of all six temperature bins are not statistically significant. Solely including the weather controls (model 3), gives only a statistically significant result for bin 6 (≥32°C), which is positive. Similar to model 1, only temperature bin 2 (16-20°C) shows a statistically significant negative coefficient and temperature bin 6 (≥32°C) a statistically significant positive coefficient, when solely WAZ-related controls are included (model 4). The weather control relative humidity and the WAZ-related control maternal education primary show negative statistically significant coefficients. This indicates that the probability of children being underweight (i.e. WAZ <-2 SD) decreases when relative humidity and the share of mothers with primary education as their highest educational level increase. The other controls are not statistically significant. The R-squared values of the models are not as high as with the fixed effects linear regression models, however, they are still relatively high suggesting a good model fit. Model 1 has the lowest R-squared value, which indicates that adding controls raises the explanatory power of the models.

TABLE 4.1.1: FIXED EFFECTS LINEAR REGRESSION MODELS, ESTIMATING WEIGHT-FOR-AGE Z SCORES

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Temperature Bin (1) <16°C	0.0096***	0.0020	0.0058**	0.0053**
	(0.0025)	(0.0027)	(0.0026)	(0.0026)
Temperature Bin (2) 16-20°C	0.0027	-0.0040	-0.0014	0.0002
	(0.0024)	(0.0028)	(0.0029)	(0.0023)
Temperature Bin (3) 20-24°C	0.0002	-0.0028*	-0.0021	-0.0001
	(0.0009)	(0.0015)	(0.0014)	(0.0010)
Temperature Bin (5) 28-32°C	-0.0015	0.0015	0.0011	-0.0014
	(0.0015)	(0.0019)	(0.0019)	(0.0015)
Temperature Bin (6) ≥32°C	-0.0052***	0.0003	-0.0022	-0.0034
	(0.0020)	(0.0028)	(0.0024)	(0.0022)
Precipitation		-0.0003***	-0.0004***	
		(0.0001)	(0.0001)	
Relative Humidity		0.0369***	0.0348***	
		(0.0117)	(0.0117)	
Wind Speed		0.3291	0.3874	
		(0.2367)	(0.2406)	
Wind Direction		-0.0018	-0.0025	
		(0.0018)	(0.0019)	
Child Age		-0.0188**		-0.0205**
		(0.0079)		(0.0083)
Refrigerator *(1=Yes)*		0.0634		0.1778
		(0.2076)		(0.2000)
Source of Drinking Water *(1=Improved)*		-0.1345		-0.1168
		(0.2455)		(0.2646)
Maternal Education Primary *(1=Primary)*		0.7939***		0.7812**
		(0.3066)		(0.3169)
Maternal Education Secondary *(1=Secondary)*		0.8678***		0.8800***
		(0.2333)		(0.2302)
Maternal Education Higher *(1=Higher)*		0.7059		0.6324
		(0.5113)		(0.4823)

Constant	-1.6317***	-3.8799***	-3.8867***	-1.4039***
	(0.2386)	(1.0503)	(0.9936)	(0.5271)
Observations	934	934	934	934
R-squared	0.8793	0.8936	0.8849	0.8892
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 4.1.2: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM), ESTIMATING PROBABILITY OF BEING UNDERWEIGHT

VARIABLES	(M1) Underweight	(M2) Underweight	(M3) Underweight	(M4) Underweight
Temperature Bin (1) <16°C	-0.0016	0.0012	-0.0005	-0.0001
	(0.0027)	(0.0030)	(0.0029)	(0.0027)
Temperature Bin (2) 16-20°C	-0.0051**	-0.0016	-0.0026	-0.0044*
	(0.0024)	(0.0025)	(0.0024)	(0.0024)
Temperature Bin (3) 20-24°C	-0.0011	0.0008	0.0008	-0.0013
	(0.0009)	(0.0015)	(0.0014)	(0.0009)
Temperature Bin (5) 28-32°C	0.0023	0.0002	0.0003	0.0024
	(0.0014)	(0.0015)	(0.0015)	(0.0014)
Temperature Bin (6) ≥32°C	0.0071***	0.0043	0.0047*	0.0072***
	(0.0024)	(0.0031)	(0.0027)	(0.0026)
Precipitation		0.0000	0.0000	
		(0.0001)	(0.0001)	
Relative Humidity		-0.0234*	-0.0216*	
		(0.0120)	(0.0115)	
Wind Speed		-0.1207	-0.1317	
		(0.2344)	(0.2241)	
Wind Direction		0.0007	0.0008	
		(0.0017)	(0.0016)	
Child Age		0.0010		0.0014
		(0.0054)		(0.0053)
Refrigerator *(1=Yes)*		0.0526		-0.0066
		(0.1683)		(0.1576)
Source of Drinking Water *(1=Improved)*		0.0202		0.0040
		(0.2021)		(0.2012)
Maternal Education Primary *(1=Primary)*		-0.8070**		-0.7907**

		(0.3676)		(0.3695)
Maternal Education Secondary *(1=Secondary)*		-0.2080		-0.1887
		(0.2614)		(0.2560)
Maternal Education Higher *(1=Higher)*		-0.1635		-0.1151
		(0.4391)		(0.4187)
Constant	-0.0029	1.6734	1.4766*	0.1046
	(0.2762)	(1.0713)	(0.8461)	(0.4062)
Observations	934	934	934	934
R-squared	0.6095	0.6186	0.6123	0.6155
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

4.2 Heterogeneity Analyses

Three heterogeneity analyses were performed in order to estimate whether the effect of rising temperatures on child nutritional status varies between subgroups. Bin 4 (24-28°C) was set as the omitted bin in all three heterogeneity analyses. Therefore, the coefficients of the other temperature bins represent the marginal effect on WAZ and the probability of being underweight, compared to a day in omitted bin 4 (24-28°C).[15]

4.2.1 Poor versus Non-Poor

In the first heterogeneity analysis, the sample is split into poor and non-poor and only investigates the effects on WAZ scores, since there is only one observation in which the average WAZ score is classified as underweight in the non-poor group, see Table 4.2.1. Lower temperatures positively affect the WAZ score for non-poor, as indicated by the statistically significant positive coefficients. For the poor group, this is observed as well in model 1 (without

[15] Hence, when the sections below refer to 'lower/higher temperatures', it represents the effect of an additional day in a lower/higher temperature bin, compared to a day with a temperature in omitted bin 4 (24-28°C).

controls), only with a smaller magnitude than the non-poor group. However, despite having a smaller magnitude than the statistically significant positive coefficient in model 1, model 2 and model 3 that include controls show statistically significant negative coefficients for temperature bin 3 (20-24°C) for the poor group. This means that lower temperatures result to higher WAZ scores (i.e. better nutritional status) for non-poor. For the poor group, lower temperatures result to higher WAZ scores (i.e. better nutritional status) when excluding controls, but with a smaller effect than for non-poor, and to lower WAZ scores (i.e. worse nutritional status) when including controls. This indicates that lower temperatures affect WAZ more negatively for the poor group than for the non-poor group. Higher temperatures affect the WAZ score for both poor and non-poor negatively (only statistically significant when excluding controls), with non-poor having a larger magnitude. This indicates that, when excluding controls, higher temperatures decrease WAZ scores (i.e. worse nutritional status) for both groups, with a larger effect for the non-poor group. This indicates that higher temperatures affect WAZ more negatively for the non-poor group than for the poor group.

TABLE 4.2.1: FIXED EFFECTS LINEAR REGRESSION MODELS, ESTIMATING WEIGHT-FOR-AGE Z SCORES – POOR VS. NON-POOR

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Non-Poor				
Temperature Bin (1) <16°C	0.0267***	0.0098	0.0191**	0.0185**
	(0.0072)	(0.0100)	(0.0096)	(0.0080)
Temperature Bin (2) 16-20°C	0.0202*	0.0070	0.0146	0.0123
	(0.0108)	(0.0114)	(0.0132)	(0.0094)
Temperature Bin (3) 20-24°C	0.0022	0.0003	0.0003	0.0023
	(0.0044)	(0.0053)	(0.0047)	(0.0045)
Temperature Bin (5) 28-32°C	-0.0083**	-0.0046	-0.0050	-0.0066
	(0.0040)	(0.0044)	(0.0045)	(0.0043)
Temperature Bin (6) ≥32°C	-0.0155	-0.0089	-0.0114	-0.0109
	(0.0098)	(0.0100)	(0.0104)	(0.0100)
Poor				
Temperature Bin (1) <16°C	0.0058*	-0.0015	0.0033	0.0013
	(0.0034)	(0.0034)	(0.0032)	(0.0035)
Temperature Bin (2) 16-20°C	0.0016	-0.0052	-0.0034	0.0005
	(0.0027)	(0.0032)	(0.0032)	(0.0027)
Temperature Bin (3) 20-24°C	0.0002	-0.0040**	-0.0030*	0.0000
	(0.0010)	(0.0017)	(0.0016)	(0.0010)
Temperature Bin (5) 28-32°C	-0.0017	0.0030	0.0022	-0.0014

	(0.0017)	(0.0022)	(0.0023)	(0.0017)
Temperature Bin (6) ≥32°C	-0.0061***	0.0014	-0.0016	-0.0041
	(0.0023)	(0.0033)	(0.0029)	(0.0026)
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

4.2.2 Rural versus Urban

The sample is divided into rural and urban to analyze whether there is a difference between the subgroups in terms of the effect of rising temperatures on child nutritional status. This heterogeneity analysis only investigates the effects on WAZ scores since there are no districts with average WAZ scores classified as underweight in the urban group, see Table 4.2.2. Lower temperatures affect the WAZ score for urban positively in model 1 (without controls). However, when controls are included, three statistically significant negative coefficients are found for temperature bin 2 (16-20°C), which have larger magnitudes than the statistically significant positive coefficient in model 1. This is also the case for rural, as lower temperatures affect WAZ score positively in model 1 (without controls). However, including controls shows in model 2 and model 3 statistically significant negative coefficients for temperature bin 3 (20-24°C). In contrast to urban, these have smaller magnitudes than the statistically significant positive coefficient in model 1. However, model 3 (including weather controls) also shows a statistically significant positive coefficient for bin 1 (<16°C); the effect size of bin 1 (<16°C) is twice as large as for bin 3 (20-24°C) in model 3. The results show that both positive and negative statistically significant coefficients have bigger effect sizes for urban than rural. This means that lower temperatures result to lower WAZ scores (i.e. worse nutritional status) for urban when including controls. For rural, lower temperatures result to both higher and lower WAZ scores when including controls, but the effect is larger for higher WAZ scores (i.e. better nutritional status). When excluding controls, the lower temperatures result to higher WAZ scores (i.e. better nutritional status) for both urban and rural. Since the effect sizes are larger for urban than for rural, lower temperatures affect WAZ more negatively for urban than for rural when including controls, and more positively for urban than for rural when excluding controls. Higher temperatures influence the WAZ score for rural negatively (only statistically significant when excluding controls); bins with higher temperatures are not statistically significant for urban. This suggests that higher temperatures result to lower WAZ scores (i.e. worse nutritional status) for rural when excluding controls. However, no conclusion can be drawn about whether rural or urban is more negatively affected by higher temperatures since urban does not have statistically significant coefficients for the higher temperature bins.

TABLE 4.2.2: FIXED EFFECTS LINEAR REGRESSION MODELS, ESTIMATING WEIGHT-FOR-AGE Z SCORES – RURAL VS. URBAN

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Urban				
Temperature Bin (1) <16°C	0.0322***	-0.0205	0.0002	0.0066
	(0.0112)	(0.0246)	(0.0205)	(0.0260)
Temperature Bin (2) 16-20°C	-0.0036	-0.0484**	-0.0333*	-0.0435*
	(0.0150)	(0.0210)	(0.0160)	(0.0216)
Temperature Bin (3) 20-24°C	0.0045	0.0027	0.0041	0.0027
	(0.0058)	(0.0057)	(0.0038)	(0.0059)
Temperature Bin (5) 28-32°C	-0.0039	0.0036	0.0007	0.0031
	(0.0064)	(0.0070)	(0.0038)	(0.0088)
Temperature Bin (6) ≥32°C	-0.0119	-0.0217	-0.0283	-0.0222
	(0.0157)	(0.0230)	(0.0203)	(0.0234)
Rural				
Temperature Bin (1) <16°C	0.0078***	0.0011	0.0048*	0.0041
	(0.0027)	(0.0029)	(0.0027)	(0.0028)
Temperature Bin (2) 16-20°C	0.0024	-0.0042	-0.0019	0.0006
	(0.0026)	(0.0030)	(0.0030)	(0.0025)
Temperature Bin (3) 20-24°C	0.0002	-0.0035**	-0.0024*	-0.0001
	(0.0009)	(0.0016)	(0.0014)	(0.0010)
Temperature Bin (5) 28-32°C	-0.0013	0.0027	0.0019	-0.0010
	(0.0016)	(0.0020)	(0.0020)	(0.0016)
Temperature Bin (6) ≥32°C	-0.0048**	0.0015	-0.0010	-0.0032
	(0.0021)	(0.0030)	(0.0025)	(0.0023)
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

4.2.3 Males versus Females

The last heterogeneity analysis examines whether the effect of rising temperatures on child nutritional status varies between males versus females, see Table 4.2.3 and Table 4.2.4. Statistically significant positive coefficients suggest that lower temperatures affect the WAZ score of males positively. For females, this is only shown in model 4 (including WAZ-related controls) where bin 1 (<16°C) has a positive coefficient that is statistically significant at the 10 percent level. In contrast, model 2 (including all controls) shows a statistically significant negative coefficient for the second bin (16-20°C) at the 1 percent level for females. This means that lower temperatures result to higher WAZ scores (i.e. better nutritional status) for males. For females both higher (model 4) and lower (model 2) WAZ scores are indicated depending on the model. Higher temperatures influence the WAZ score of males negatively (only statistically significant when excluding controls), while this effect is shown to be positive for females (only statistically significant positive coefficient when including all controls). Meaning that higher temperatures lead to lower WAZ scores (i.e. worse nutritional status) for males and higher WAZ scores (i.e. better nutritional status) for females. This indicates that higher temperatures affect WAZ more negatively for males than for females.

Additionally, higher temperatures influence the probability of being underweight for males positively, as indicated by the statistically significant positive coefficients; bins with lower temperatures are not statistically significant for males. This means that higher temperatures increases the probability of being underweight for males. As indicated by the statistically significant negative coefficients when including controls, both lower and higher temperatures influence the probability of being underweight for females negatively. However, the coefficients for the lower temperatures show slightly larger effect sizes. This implies that lower temperatures decreases the probability of being underweight for females more than higher temperatures. Therefore, the results show that higher temperatures affect the probability of being underweight more negatively for females than for males.

TABLE 4.2.3: FIXED EFFECTS LINEAR REGRESSION MODELS, ESTIMATING WEIGHT-FOR-AGE Z SCORES – MALES VS. FEMALES

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Males				
Temperature Bin (1) <16°C	0.0123***	0.0049	0.0082**	0.0085**
	(0.0034)	(0.0037)	(0.0035)	(0.0033)
Temperature Bin (2) 16-20°C	0.0010	-0.0038	-0.0025	-0.0000
	(0.0035)	(0.0039)	(0.0041)	(0.0033)
Temperature Bin (3) 20-24°C	0.0016	-0.0003	0.0002	0.0014
	(0.0015)	(0.0021)	(0.0019)	(0.0016)
Temperature Bin (5) 28-32°C	-0.0027	-0.0002	-0.0007	-0.0025
	(0.0020)	(0.0024)	(0.0026)	(0.0019)
Temperature Bin (6) ≥32°C	-0.0047*	-0.0005	-0.0028	-0.0030
	(0.0027)	(0.0036)	(0.0032)	(0.0030)
Females				
Temperature Bin (1) <16°C	0.0075	0.0086	0.0023	0.0146*
	(0.0119)	(0.0078)	(0.0116)	(0.0086)
Temperature Bin (2) 16-20°C	0.0021	-0.0121***	-0.0033	-0.0045
	(0.0039)	(0.0036)	(0.0047)	(0.0038)
Temperature Bin (3) 20-24°C	0.0015	-0.0054	-0.0009	0.0006
	(0.0023)	(0.0036)	(0.0031)	(0.0024)
Temperature Bin (5) 28-32°C	-0.0053	0.0111*	-0.0027	0.0031
	(0.0044)	(0.0061)	(0.0061)	(0.0049)
Temperature Bin (6) ≥32°C	-0.0036	0.0228**	-0.0018	0.0129
	(0.0084)	(0.0109)	(0.0103)	(0.0088)
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 4.2.4: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM), ESTIMATING PROBABILITY OF BEING UNDERWEIGHT – MALES VS. FEMALES

VARIABLES	(M1) Underweight	(M2) Underweight	(M3) Underweight	(M4) Underweight
Males				

Temperature Bin (1) <16°C	-0.0004	0.0010	0.0009	-0.0002
	(0.0031)	(0.0037)	(0.0035)	(0.0032)
Temperature Bin (2) 16-20°C	-0.0026	-0.0003	-0.0003	-0.0028
	(0.0027)	(0.0027)	(0.0025)	(0.0028)
Temperature Bin (3) 20-24°C	-0.0006	0.0007	0.0012	-0.0010
	(0.0011)	(0.0019)	(0.0018)	(0.0013)
Temperature Bin (5) 28-32°C	0.0031	0.0015	0.0012	0.0033*
	(0.0019)	(0.0020)	(0.0020)	(0.0019)
Temperature Bin (6) ≥32°C	0.0090***	0.0072**	0.0069**	0.0095***
	(0.0028)	(0.0036)	(0.0032)	(0.0031)
Females				
Temperature Bin (1) <16°C	-0.0231	-0.0247*	-0.0219	-0.0262*
	(0.0144)	(0.0128)	(0.0138)	(0.0142)
Temperature Bin (2) 16-20°C	-0.0053	0.0039	-0.0017	-0.0024
	(0.0039)	(0.0049)	(0.0029)	(0.0041)
Temperature Bin (3) 20-24°C	-0.0022	0.0038	0.0013	-0.0032
	(0.0017)	(0.0035)	(0.0019)	(0.0024)
Temperature Bin (5) 28-32°C	-0.0029	-0.0208**	-0.0074	-0.0095*
	(0.0026)	(0.0096)	(0.0052)	(0.0050)
Temperature Bin (6) ≥32°C	-0.0046	-0.0282**	-0.0107	-0.0128
	(0.0046)	(0.0131)	(0.0076)	(0.0076)
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

4.3 Robustness Checks

To test the robustness of the main results, a different set of fixed effects is included in model 1 (without controls) and model 2 (including both weather and WAZ-related controls), see Table 8.3.1 and Table 8.3.2. Column (3) and column (4) replace wave fixed effects with state fixed effects to control for unobserved and time-invariant effects of state characteristics. This robustness check supports the main results for estimating both WAZ scores and the probability of being underweight, since the same statistical significance is found, with only small increases in the effect sizes for WAZ and slight reductions in the probability of being underweight when state fixed effects are included.

Additionally, to check whether the main results are vulnerable to the omitted bin choice, the models are run with bin 3 (20-24°C) and bin 6 (≥32°C) as alternative omitted bins instead of bin 4 (24-28°C), because bin 3 (20-24°C) has the most optimal weather temperature for humans and bin 6 (≥32°C) has the highest temperature, see Table 8.3.3 to Table 8.3.6 (Asseng et al., 2021). Using bin 3 (20-24°C) as omitted bin shows the same results for WAZ as bin 4 (24-28°C), with only slightly different effect sizes. Even though the results for the probability of being underweight are a bit different, the results still only show negative statistical significance for the temperature bins below the omitted bin, and positive statistical significance for the temperature bins above the omitted bin, resembling the main results with omitted bin 4 (24-28°C). Similar findings for WAZ and the probability of being underweight are found when temperature bin 6 (≥32°C) is utilized as the omitted bin rather than bin 4 (24–28°C); the WAZ coefficient becomes more positive and the probability of being underweight coefficient becomes more negative as temperature decreases. Therefore, the temperature effects are insensitive to the omitted bin choice.

The regression models are also performed without the weather control relative humidity as a robustness check, since this control shows to be highly correlated to temperature bin 6 (≥32°C), see Table 8.3.7 and Table 8.3.8. For the main results, relative humidity is included in model 2 and model 3, see Table 4.1.1 and Table 4.1.2. The results for WAZ when including relative humidity in model 2 only shows a statistically significant coefficient for bin 3 (20-24°C), which is negative, while bin 1 (<16°C) is the only statistically significant coefficient in model 3, which is positive. However, without relative humidity in the models, the sign of bin 3 (20-24°C) changes in model 2 and model 3, but is not statistically significant, in contrast to bin 3 (20-24°C) in model 2 when including relative humidity. However, without relative humidity, model 2 shows a statistically significant negative coefficient for bin 6 (≥32°C), which is similar to model 1 (without controls) when including relative humidity. Model 3 still shows a positive significance for bin 1 (<16°C) when relative humidity is excluded, only with a larger magnitude. In addition, temperature bin 6 (≥32°C) shows negative statistical significance. The statistical significance of the controls do not change, however the coefficients of the statistically significant controls become less positive or more negative, except for precipitation, whose coefficient remains the same. The results for the probability of being underweight when including relative humidity are not statistically significant in model 2, while in model 3 only bin 6 (≥32°C) is statistically significant, which is positive. However, without relative humidity in the models, bin 2 (16-20°C) and bin 6 (≥32°C) become negatively and positively statistically significant in model 2, which is similar to model 1 (without controls) when including relative humidity. Model 3 still shows a positive significance for bin 6 (≥32°C) when relative humidity is excluded, only at a lower percent level and with a larger magnitude. Additionally, temperature bin 2 (16-20°C) is negative statistically significant, which is similar to model 1 (without controls) when including relative humidity. The results of the controls do not change when excluding relative humidity. Overall, this indicates that the results without including relative humidity are similar to model 1, which includes no controls at all; i.e. the statistically significant coefficients are only negative for temperature bins above omitted bin 4 (24-28°C), and only positive for temperature bins below the omitted bin when estimating WAZ scores, and vice versa when estimating the probability of being underweight.

As stated in section 3.2, a robustness check with severely underweight (i.e. WAZ <-3 SD) was considered as well, but not able to perform since no district is severely underweight.

5 Discussion

Analyses were conducted to examine how increasing temperatures affect children's nutritional status in India, as literature (e.g. Biswas et al., 2024; Ebi & Paulson, 2007) suggests that rising temperatures negatively affect children's health through several channels. It was found that results lose statistical significance once controls are included when estimating WAZ scores and the probability of being underweight (i.e. WAZ <-2 SD).

Thus, when estimating WAZ scores as well as the probability of being underweight without including controls, only the effects of two temperature bins (increase WAZ score by 0.0096 SD for temperature bin 1 (<16°C) and decrease by 0.0052 SD for temperature bin 6 (≥32°C)) are statistically significant and align with expected results according to existing literature (e.g. Algur et al., 2021; Biswas et al., 2024; Ebi & Paulson, 2007; Motarjemi et al., 1993), i.e. lower/decreasing temperatures increase WAZ scores and decrease the probability of being underweight, while higher/increasing temperatures decrease WAZ scores and increase the probability of being underweight. Too put this in value terms, compared to a day with a temperature in omitted bin 4 (24-28°C), an additional day in bin 1 (<16°C) increases the weight of 30-month-old males by 12 grams (+0.11%), while an additional day in bin 6 (≥32°C) decreases it by 7 grams (-0.06%). Although these effect sizes and these corresponding values when excluding controls are small, multiple additional days per year with temperatures in these bins may result in substantial changes in WAZ scores and therefore children's nutritional status.

However, including both weather and WAZ-related controls produces results that are not statistically significant anymore; estimating WAZ scores solely shows a statistical significant relation with temperature bin 3 (20-24°C), which is negative (-0.0028), indicating that an extra day in bin 3 (20-24°C) decreases WAZ scores (i.e. worse nutritional status) compared to an additional day in bin 4 (24-28°C). In value terms, compared to a day with a temperature in omitted bin 4 (24-28°C), an additional day in bin 3 (20-24°C) decreases the weight of 30-month-old males by 4 grams (-0.04%). Estimating the probability of being underweight including controls results in no statistically significant results.

Therefore, the findings do not align with expectations based on existing literature, which indicates that rising temperatures influence children's health negatively through multiple channels (e.g. Algur et al., 2021; Biswas et al., 2024; Ebi & Paulson, 2007; Motarjemi et al., 1993). Given that the results are no longer statistically significant when including controls that are suggested by existing literature (e.g. Biswas et al., 2024; Chen & Yang, 2019), suggests that the effects found without controls are (partly) explained by other elements instead of temperature only. Hence, the null hypothesis of H_1, which states that rising temperatures negatively affect children's nutritional status in India, cannot be rejected.

Heterogeneity analyses indicate that, when including weather and WAZ-related controls, there are no statistical significant effects that suggest that the effect of rising temperatures on the nutritional status of children is more negative for poor people and people living in rural areas than for non-poor people and people living in urban areas. A more negative effect for females than for males was only found for the effect on the probability of being underweight, not for the effect on WAZ scores; i.e. higher temperatures affect the probability of being underweight more negatively for females than for males. These results are not in line with expectations based on existing literature (e.g. Biswas et al., 2024; Burgess et al., 2017; Mitra, 2014). Therefore, the null hypotheses of H2, H3 and H4 cannot be rejected. The results for the statistically significant controls for the main results are like expected based on previous literature, except for the weather control relative humidity (e.g. Biswas et al., 2024; Ebi & Paulson, 2007; Zhang et al., 2023). However, the findings imply a larger positive effect on WAZ scores when the highest maternal educational level is primary as opposed to secondary, which is not like expected (Biswas et al., 2024). Robustness checks that used different sets of fixed effects and alternative omitted bins were found to support the main results when estimating both WAZ scores and the probability of being underweight. Excluding the weather control relative humidity as robustness check, due to its correlation with temperature bin 6, gives results that are similar to model 1, which includes no controls at all. However, according to existing literature (e.g. sources) it is important to include this weather control.

This study also has some limitations that have to be mentioned. As the NFHS health data captures values from different households each wave, and not every district is surveyed every year within each NFHS wave. Therefore, the data is aggregated at the district and wave level in order to create a panel. However, district identifications are only included in the NFHS-4 and NFHS-5 data. Therefore, solely these two waves were able to use for the sample, leading to a relatively low sample. However, in terms of data availability, NFHS was the most optimal dataset to use for this study. Using a district-wave panel means that the WAZ scores are averages of the households in each district, which removes within-district variation and resulted in WAZ scores solely above minus three, i.e. it removes WAZ scores from the sample that are classified as severely underweight. However, the necessity to drop several districts from the sample enabling merging NFHS-4, NFHS-5 and the weather data does not lead to a substantial different percentage of districts that show WAZ scores classified as underweight (i.e. WAZ <-2) and severely underweight (i.e. WAZ <-3). Furthermore, the subgroups used for the heterogeneity analyses are largely imbalanced, which could have affected the results and therefore its reliability.

Therefore, further research should be done using a household sample with a larger number of observations and covering more than two years, to investigate whether these limitations are the reason no statistically significant effect was found between rising temperatures and children's nutritional status in India. Furthermore, research could be conducted with other weather variables, such as wet bulb and heat index which is as suggested by Geruso and Spears (2018) and Zhang et al. (2018); as this data was beyond my access. Using a binned temperature approach for other weather variables, similar to Graff Zivin et al. (2020), may also lead to insightful information. In addition, future research could utilize lagged effects in order to analyze whether children's nutritional status is affected by temperature in prior years. Performing heterogeneity analyses to investigate whether the effect is different between several regions allow for a deeper understanding of variations of the possible effect across regions in India, which may provide insightful information for policymakers when determining whether region-specific policy interventions are necessary in India to deal with the effect of rising temperatures on underweight prevalence among Indian children. Since this study did not find a statistically significant effect between rising temperatures and children's nutritional status in India no concrete recommendations for policy can be formed.

6 Conclusion

This study investigated how rising temperatures affect the nutritional status of children under five in India, in order to examine whether the increasing temperatures (Mourougan et al., 2024) and the prevalence of child malnutrition (Das et al., 2021; Tripathi et al., 2023) in this developing country are related. Existing literature indicates that increasing temperatures influence (children's) health and nutritional status negatively through multiple channels: agriculture, income, worker productivity, worker absenteeism, diseases, and contamination of both food and water (e.g. Bharambe et al., 2023; Biswas et al., 2024; Ebi & Paulson, 2007; Motarjemi et al., 1993).

Nutritional status is measured by weight-for-age Z scores (WAZ), which is also used to examine how rising temperatures affect the probability of children being underweight (WAZ <-2). WAZ and other health-related data from NFHS-4 and NFHS-5 are combined with weather data (i.e. daily temperatures, precipitation, relative humidity, wind speed and wind direction) from ERA5, and create a district-wave panel with 467 districts in total across the two waves. A binned temperature approach is utilized, where each bin has a width of 4°C and represents the number of days averaged across the 467 districts and waves with a daily average temperature that falls within one of the six defined bins (<16°C to ≥32°C); bin 4 (24-28°C) is used as the reference group. Both fixed effects linear regression models and fixed effects Linear Probability Models (LPM) are employed with weather and WAZ-related controls, in order to perform analyses with the continuous variable WAZ and the binary variable $Underweight$.

However, the findings do not align with expectations based on existing literature, which indicates that rising temperatures influence children's health negatively through multiple channels (e.g. Algur et al., 2021; Biswas et al., 2024; Ebi & Paulson, 2007; Motarjemi et al., 1993). Hence, the null hypothesis of H_1, which states that rising temperatures negatively affect children's nutritional status in India, cannot be rejected. Heterogeneity analyses indicate that there are no statistical significant effects that suggest that the effect of rising temperatures on the nutritional status of children is more negative for poor people, people living in rural areas and females than for non-poor people, people living in urban areas and males.

Since this study has some limitations, further research should be done using a household sample with a larger number of observations and covering more than two years, to investigate whether these limitations are the reason no statistically significant effect was found between rising temperatures and children's nutritional status in India.

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8 Appendices

8.1 Data and Methodology

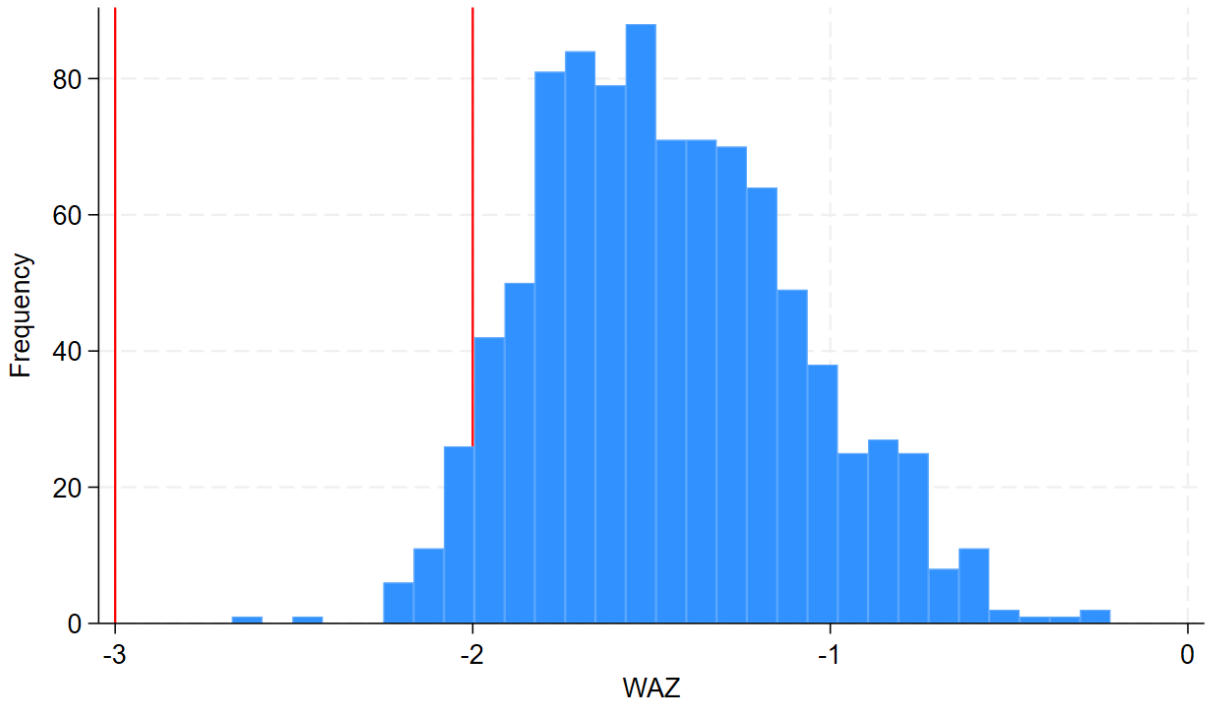

FIGURE 8.1.1: DISTRIBUTION OF THE WAZ SCORES (934 OBSERVATIONS FROM 467 DISTRICTS ACROSS THE TWO WAVES)

Notes: <-2 is underweight; <-3 is severely underweight.

TABLE 8.1.1: SUMMARY STATISTICS

VARIABLES	N	Percentage (%)	Mean	Std. Dev.	Min	Max
WAZ	**934**	**100%**	-1.453	.363	-2.673	-.217
Underweight	**934**	**100%**	.044	.205	0	1
No *(=0=reference group)*	893	95.61%				
Yes *(=1)*	41	4.39%				
Temperature Bin (1) <16°C	**934**	**100%**	33.349	59.305	0	353
Temperature Bin (2) 16-20°C	**934**	**100%**	36.638	25.527	0	157
Temperature Bin (3) 20-24°C	**934**	**100%**	66.064	45.59	0	299
Temperature Bin (4) 24-28°C	**934**	**100%**	116.757	60.651	0	335.667
Temperature Bin (5) 28-32°C	**934**	**100%**	74.557	43.562	0	213
Temperature Bin (6) ≥32°C	**934**	**100%**	25.635	23.69	0	131.333
Precipitation	**934**	**100%**	345.376	202.896	41.971	1615.212
Relative Humidity	**934**	**100%**	65.922	8.845	42.822	86.237
Wind Speed	**934**	**100%**	1.726	.668	.261	4.538
Wind Direction	**934**	**100%**	169.966	27.255	71.994	281.002
Child Age	**934**	**100%**	30.297	1.389	13	36.835
Refrigerator	**934**	**100%**	.319	.251	0	1
Source of Drinking Water	**934**	**100%**	.926	.102	.333	1
Maternal Education No Education	**934**	**100%**	.219	.177	0	.779
Maternal Education Primary	**934**	**100%**	.128	.063	0	.403
Maternal Education Secondary	**934**	**100%**	.518	.156	.124	.977
Maternal Education Higher	**934**	**100%**	.136	.111	0	.683
Wealth Index	**934**	**100%**	1.834	.866	0	4
Poor *(=0=reference group)*	715	76.55%				
Non-Poor *(=1)*	219	23.45%				
Urban	**934**	**100%**	.085	.278	0	1
Rural *(=0=reference group)*	855	91.54%				
Urban *(=1)*	79	8.46%				
Sex	**934**	**100%**	.734	.442	0	1
Female *(=0=reference group)*	248	26.55%				
Male *(=1)*	686	73.45%				

8.2 Multicollinearity Tests

TABLE 8.2.1: VARIANCE INFLATION VECTOR (VIF), WAZ AS DEPENDENT VARIABLE

VARIABLE	VIF	1/VIF
Relative Humidity	6.171	.162
Temperature Bin (6) ≥32°C	3.91	.256
Wind Speed	3.472	.288
Temperature Bin (5) 28-32°C	3.383	.296
Maternal Education Higher *(=1=Higher)*	3.25	.308
Precipitation	2.753	.363
Refrigerator *(=1=Yes)*	2.544	.393
Temperature Bin (3) 20-24°C	2.239	.447
Maternal Education Higher *(=1=Primary)*	2.035	.491
Temperature Bin (1) <16°C	1.991	.502
Temperature Bin (2) 16-20°C	1.974	.507
Maternal Education Higher *(=1=Secondary)*	1.854	.54
Source of Drinking Water *(=1=Improved)*	1.453	.688
Wind Direction	1.361	.735
Child Age	1.083	.923
Mean VIF	2.631	.

8.3 Robustness Checks

8.3.1 Fixed Effects

TABLE 8.3.1: FIXED EFFECTS LINEAR REGRESSION MODELS WITH STATE FIXED EFFECTS, ESTIMATING WEIGHT-FOR-AGE Z SCORES

VARIABLES	(1) WAZ	(2) WAZ	(3) WAZ	(4) WAZ
Temperature Bin (1) <16°C	0.0096***	0.0020	0.0129***	0.0030
	(0.0025)	(0.0027)	(0.0022)	(0.0026)
Temperature Bin (2) 16-20°C	0.0027	-0.0040	0.0048*	-0.0039
	(0.0024)	(0.0028)	(0.0024)	(0.0028)
Temperature Bin (3) 20-24°C	0.0002	-0.0028*	0.0009	-0.0030**
	(0.0009)	(0.0015)	(0.0009)	(0.0015)
Temperature Bin (5) 28-32°C	-0.0015	0.0015	-0.0017	0.0019
	(0.0015)	(0.0019)	(0.0015)	(0.0019)
Temperature Bin (6) ≥32°C	-0.0052***	0.0003	-0.0058***	0.0007
	(0.0020)	(0.0028)	(0.0020)	(0.0027)
Precipitation		-0.0003***		-0.0002**
		(0.0001)		(0.0001)
Relative Humidity		0.0369***		0.0395***
		(0.0117)		(0.0114)
Wind Speed		0.3291		0.2784
		(0.2367)		(0.2367)
Wind Direction		-0.0018		-0.0021
		(0.0018)		(0.0018)
Child Age		-0.0188**		-0.0190**
		(0.0079)		(0.0080)
Refrigerator *(1=Yes)*		0.0634		0.1194
		(0.2076)		(0.2220)
Source of Drinking Water *(1=Improved)*		-0.1345		-0.1180
		(0.2455)		(0.2483)
Maternal Education Primary *(1=Primary)*		0.7939***		0.8038**
		(0.3066)		(0.3135)
Maternal Education Secondary *(1=Secondary)*		0.8678***		0.9092***
		(0.2333)		(0.2229)
Maternal Education Higher *(1=Higher)*		0.7059		0.7582
		(0.5113)		(0.5011)
Constant	-1.6317***	-3.8799***	-1.8429***	-4.0622***
	(0.2386)	(1.0503)	(0.2394)	(1.0206)
Observations	934	934	934	934
R-squared	0.8793	0.8936	0.8780	0.8933
Weather Controls	No	Yes	No	Yes

WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	No	No
State FE	No	No	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 8.3.2: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM) WITH STATE FIXED EFFECTS, ESTIMATING PROBABILITY OF BEING UNDERWEIGHT

VARIABLES	(1) Underweight	(2) Underweight	(3) Underweight	(4) Underweight
Temperature Bin (1) <16°C	-0.0016	0.0012	-0.0002	0.0017
	(0.0027)	(0.0030)	(0.0022)	(0.0029)
Temperature Bin (2) 16-20°C	-0.0051**	-0.0016	-0.0042*	-0.0016
	(0.0024)	(0.0025)	(0.0022)	(0.0025)
Temperature Bin (3) 20-24°C	-0.0011	0.0008	-0.0007	0.0007
	(0.0009)	(0.0015)	(0.0009)	(0.0014)
Temperature Bin (5) 28-32°C	0.0023	0.0002	0.0022	0.0003
	(0.0014)	(0.0015)	(0.0015)	(0.0016)
Temperature Bin (6) ≥32°C	0.0071***	0.0043	0.0069***	0.0045
	(0.0024)	(0.0031)	(0.0024)	(0.0031)
Precipitation		0.0000		0.0001
		(0.0001)		(0.0001)
Relative Humidity		-0.0234*		-0.0223*
		(0.0120)		(0.0119)
Wind Speed		-0.1207		-0.1413
		(0.2344)		(0.2318)
Wind Direction		0.0007		0.0006
		(0.0017)		(0.0017)
Child Age		0.0010		0.0009
		(0.0054)		(0.0055)
Refrigerator *(1=Yes)*		0.0526		0.0753
		(0.1683)		(0.1775)
Source of Drinking Water *(1=Improved)*		0.0202		0.0269
		(0.2021)		(0.2048)
Maternal Education Primary *(1=Primary)*		-0.8070**		-0.8030**
		(0.3676)		(0.3735)
Maternal Education Secondary *(1=Secondary)*		-0.2080		-0.1912
		(0.2614)		(0.2534)
Maternal Education Higher *(1=Higher)*		-0.1635		-0.1423

		(0.4391)		(0.4246)
Constant	-0.0029	1.6734	-0.0911	1.5991
	(0.2762)	(1.0713)	(0.2646)	(1.0644)
Observations	934	934	934	934
R-squared	0.6095	0.6186	0.6088	0.6185
Weather Controls	No	Yes	No	Yes
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	No	No
State FE	No	No	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

8.3.2 Bin 3 (20-24°C) and Bin 6 (≥32°C) as Omitted Bin

TABLE 8.3.3: FIXED EFFECTS LINEAR REGRESSION MODELS WITH BIN 3 AS OMITTED BIN, ESTIMATING WEIGHT-FOR-AGE Z SCORES

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Temperature Bin (1) <16°C	0.0094***	0.0048*	0.0079***	0.0054**
	(0.0023)	(0.0028)	(0.0026)	(0.0026)
Temperature Bin (2) 16-20°C	0.0025	-0.0011	0.0006	0.0004
	(0.0025)	(0.0026)	(0.0027)	(0.0023)
Temperature Bin (4) 24-28°C	-0.0002	0.0028*	0.0021	0.0001
	(0.0009)	(0.0015)	(0.0014)	(0.0010)
Temperature Bin (5) 28-32°C	-0.0017	0.0043	0.0031	-0.0013
	(0.0018)	(0.0030)	(0.0028)	(0.0018)
Temperature Bin (6) ≥32°C	-0.0054**	0.0031	-0.0001	-0.0033
	(0.0021)	(0.0037)	(0.0031)	(0.0023)
Precipitation		-0.0003***	-0.0004***	
		(0.0001)	(0.0001)	
Relative Humidity		0.0369***	0.0348***	
		(0.0117)	(0.0117)	
Wind Speed		0.3291	0.3874	
		(0.2367)	(0.2406)	
Wind Direction		-0.0018	-0.0025	
		(0.0018)	(0.0019)	

Child Age		-0.0188**		-0.0205**
		(0.0079)		(0.0083)
Refrigerator *(1=Yes)*		0.0634		0.1778
		(0.2076)		(0.2000)
Source of Drinking Water *(1=Improved)*		-0.1345		-0.1168
		(0.2455)		(0.2646)
Maternal Education Primary *(1=Primary)*		0.7939***		0.7812**
		(0.3066)		(0.3169)
Maternal Education Secondary *(1=Secondary)*		0.8678***		0.8800***
		(0.2333)		(0.2302)
Maternal Education Higher *(1=Higher)*		0.7059		0.6324
		(0.5113)		(0.4823)
Constant	-1.5778***	-4.8703***	-4.6122***	-1.4474***
	(0.3070)	(1.3581)	(1.2871)	(0.5312)
Observations	934	934	934	934
R-squared	0.8793	0.8936	0.8849	0.8892
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 3 (20-24°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (20-24°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 8.3.4: FIXED EFFECTS LINEAR REGRESSION MODELS WITH BIN 6 AS OMITTED BIN, ESTIMATING WEIGHT-FOR-AGE Z SCORES

	(M1)	(M2)	(M3)	(M4)
VARIABLES	WAZ	WAZ	WAZ	WAZ
Temperature Bin (1) <16°C	0.0148***	0.0016	0.0080***	0.0087***
	(0.0026)	(0.0032)	(0.0029)	(0.0024)
Temperature Bin (2) 16-20°C	0.0079***	-0.0043	0.0007	0.0037
	(0.0029)	(0.0042)	(0.0042)	(0.0026)
Temperature Bin (3) 20-24°C	0.0054**	-0.0031	0.0001	0.0033
	(0.0021)	(0.0037)	(0.0031)	(0.0023)
Temperature Bin (4) 24-28°C	0.0052***	-0.0003	0.0022	0.0034
	(0.0020)	(0.0028)	(0.0024)	(0.0022)
Temperature Bin (5) 28-32°C	0.0037**	0.0012	0.0033**	0.0020
	(0.0015)	(0.0020)	(0.0015)	(0.0020)
Precipitation		-0.0003***	-0.0004***	
		(0.0001)	(0.0001)	

Relative Humidity		0.0369***	0.0348***	
		(0.0117)	(0.0117)	
Wind Speed		0.3291	0.3874	
		(0.2367)	(0.2406)	
Wind Direction		-0.0018	-0.0025	
		(0.0018)	(0.0019)	
Child Age		-0.0188**		-0.0205**
		(0.0079)		(0.0083)
Refrigerator *(1=Yes)*		0.0634		0.1778
		(0.2076)		(0.2000)
Source of Drinking Water *(1=Improved)*		-0.1345		-0.1168
		(0.2455)		(0.2646)
Maternal Education Primary *(1=Primary)*		0.7939***		0.7812**
		(0.3066)		(0.3169)
Maternal Education Secondary *(1=Secondary)*		0.8678***		0.8800***
		(0.2333)		(0.2302)
Maternal Education Higher *(1=Higher)*		0.7059		0.6324
		(0.5113)		(0.4823)
Constant	-3.4817***	-3.7643***	-4.6570***	-2.6137***
	(0.5559)	(0.8374)	(0.8411)	(0.6738)
Observations	934	934	934	934
R-squared	0.8793	0.8936	0.8849	0.8892
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 6 (≥32°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (≥32°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 8.3.5: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM) WITH BIN 3 AS OMITTED BIN, ESTIMATING PROBABILITY OF BEING UNDERWEIGHT

VARIABLES	(M1) Underweight	(M2) Underweight	(M3) Underweight	(M4) Underweight
Temperature Bin (1) <16°C	-0.0005	0.0005	-0.0013	0.0013
	(0.0024)	(0.0028)	(0.0026)	(0.0026)
Temperature Bin (2) 16-20°C	-0.0040*	-0.0024	-0.0034	-0.0030
	(0.0022)	(0.0024)	(0.0023)	(0.0023)
Temperature Bin (4) 24-28°C	0.0011	-0.0008	-0.0008	0.0013
	(0.0009)	(0.0015)	(0.0014)	(0.0009)

Temperature Bin (5) 28-32°C	0.0034**	-0.0006	-0.0006	0.0037**
	(0.0016)	(0.0023)	(0.0023)	(0.0016)
Temperature Bin (6) ≥32°C	0.0082***	0.0036	0.0038	0.0085***
	(0.0024)	(0.0039)	(0.0034)	(0.0027)
Precipitation		0.0000	0.0000	
		(0.0001)	(0.0001)	
Relative Humidity		-0.0234*	-0.0216*	
		(0.0120)	(0.0115)	
Wind Speed		-0.1207	-0.1317	
		(0.2344)	(0.2241)	
Wind Direction		0.0007	0.0008	
		(0.0017)	(0.0016)	
Child Age		0.0010		0.0014
		(0.0054)		(0.0053)
Refrigerator *(1=Yes)*		0.0526		-0.0066
		(0.1683)		(0.1576)
Source of Drinking Water *(1=Improved)*		0.0202		0.0040
		(0.2021)		(0.2012)
Maternal Education Primary *(1=Primary)*		-0.8070**		-0.7907**
		(0.3676)		(0.3695)
Maternal Education Secondary *(1=Secondary)*		-0.2080		-0.1887
		(0.2614)		(0.2560)
Maternal Education Higher *(1=Higher)*		-0.1635		-0.1151
		(0.4391)		(0.4187)
Constant	-0.3755	1.9383	1.7671	-0.3594
	(0.2867)	(1.3657)	(1.1532)	(0.3949)
Observations	934	934	934	934
R-squared	0.6095	0.6186	0.6123	0.6155
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 3 (20-24°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (20-24°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 8.3.6: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM) WITH BIN 6 AS OMITTED BIN, ESTIMATING PROBABILITY OF BEING UNDERWEIGHT

	(M1)	(M2)	(M3)	(M4)
VARIABLES	Underweight	Underweight	Underweight	Underweight

Temperature Bin (1) <16°C	-0.0087***	-0.0031	-0.0052	-0.0072***
	(0.0024)	(0.0037)	(0.0032)	(0.0026)
Temperature Bin (2) 16-20°C	-0.0122***	-0.0060	-0.0072**	-0.0115***
	(0.0029)	(0.0040)	(0.0034)	(0.0031)
Temperature Bin (3) 20-24°C	-0.0082***	-0.0036	-0.0038	-0.0085***
	(0.0024)	(0.0039)	(0.0034)	(0.0027)
Temperature Bin (4) 24-28°C	-0.0071***	-0.0043	-0.0047*	-0.0072***
	(0.0024)	(0.0031)	(0.0027)	(0.0026)
Temperature Bin (5) 28-32°C	-0.0048**	-0.0042*	-0.0044**	-0.0048**
	(0.0020)	(0.0025)	(0.0020)	(0.0024)
Precipitation		0.0000	0.0000	
		(0.0001)	(0.0001)	
Relative Humidity		-0.0234*	-0.0216*	
		(0.0120)	(0.0115)	
Wind Speed		-0.1207	-0.1317	
		(0.2344)	(0.2241)	
Wind Direction		0.0007	0.0008	
		(0.0017)	(0.0016)	
Child Age		0.0010		0.0014
		(0.0054)		(0.0053)
Refrigerator *(1=Yes)*		0.0526		-0.0066
		(0.1683)		(0.1576)
Source of Drinking Water *(1=Improved)*		0.0202		0.0040
		(0.2021)		(0.2012)
Maternal Education Primary *(1=Primary)*		-0.8070**		-0.7907**
		(0.3676)		(0.3695)
Maternal Education Secondary *(1=Secondary)*		-0.2080		-0.1887
		(0.2614)		(0.2560)
Maternal Education Higher *(1=Higher)*		-0.1635		-0.1151
		(0.4391)		(0.4187)
Constant	2.5103***	3.2068***	3.1193***	2.6408***
	(0.6690)	(0.8948)	(0.8047)	(0.7834)
Observations	934	934	934	934
R-squared	0.6095	0.6186	0.6123	0.6155
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 6 (≥32°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (≥32°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

8.3.3 Without Relative Humidity as Weather Control

TABLE 8.3.7: FIXED EFFECTS LINEAR REGRESSION MODELS WITHOUT RELATIVE HUMIDITY AS WEATHER CONTROL, ESTIMATING WEIGHT-FOR-AGE Z SCORES

VARIABLES	(M1) WAZ	(M2) WAZ	(M3) WAZ	(M4) WAZ
Temperature Bin (1) <16°C	0.0096***	0.0034	0.0070***	0.0053**
	(0.0025)	(0.0027)	(0.0026)	(0.0026)
Temperature Bin (2) 16-20°C	0.0027	0.0003	0.0026	0.0002
	(0.0024)	(0.0024)	(0.0024)	(0.0023)
Temperature Bin (3) 20-24°C	0.0002	0.0004	0.0010	-0.0001
	(0.0009)	(0.0011)	(0.0011)	(0.0010)
Temperature Bin (5) 28-32°C	-0.0015	-0.0019	-0.0023	-0.0014
	(0.0015)	(0.0015)	(0.0014)	(0.0015)
Temperature Bin (6) ≥32°C	-0.0052***	-0.0042*	-0.0062***	-0.0034
	(0.0020)	(0.0022)	(0.0020)	(0.0022)
Precipitation		-0.0003***	-0.0004***	
		(0.0001)	(0.0001)	
Wind Speed		0.0516	0.1373	
		(0.2352)	(0.2320)	
Wind Direction		-0.0004	-0.0012	
		(0.0017)	(0.0017)	
Child Age		-0.0192**		-0.0205**
		(0.0082)		(0.0083)
Refrigerator *(1=Yes)*		0.1528		0.1778
		(0.2028)		(0.2000)
Source of Drinking Water *(1=Improved)*		-0.1042		-0.1168
		(0.2600)		(0.2646)
Maternal Education Primary *(1=Primary)*		0.7802**		0.7812**
		(0.3148)		(0.3169)
Maternal Education Secondary *(1=Secondary)*		0.8299***		0.8800***
		(0.2320)		(0.2302)
Maternal Education Higher *(1=Higher)*		0.6523		0.6324
		(0.5012)		(0.4823)
Constant	-1.6317***	-1.2399*	-1.4036**	-1.4039***
	(0.2386)	(0.7462)	(0.5623)	(0.5271)
Observations	934	934	934	934
R-squared	0.8793	0.8912	0.8827	0.8892
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes

District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on WAZ of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

TABLE 8.3.8: FIXED EFFECTS LINEAR PROBABILITY MODELS (LPM) WITHOUT RELATIVE HUMIDITY AS WEATHER CONTROL, ESTIMATING PROBABILITY OF BEING UNDERWEIGHT

VARIABLES	(M1) Underweight	(M2) Underweight	(M3) Underweight	(M4) Underweight
Temperature Bin (1) <16°C	-0.0016	0.0003	-0.0012	-0.0001
	(0.0027)	(0.0029)	(0.0029)	(0.0027)
Temperature Bin (2) 16-20°C	-0.0051**	-0.0044*	-0.0051**	-0.0044*
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Temperature Bin (3) 20-24°C	-0.0011	-0.0013	-0.0011	-0.0013
	(0.0009)	(0.0011)	(0.0010)	(0.0009)
Temperature Bin (5) 28-32°C	0.0023	0.0023*	0.0023*	0.0024
	(0.0014)	(0.0013)	(0.0013)	(0.0014)
Temperature Bin (6) ≥32°C	0.0071***	0.0072***	0.0072***	0.0072***
	(0.0024)	(0.0026)	(0.0024)	(0.0026)
Precipitation		0.0000	0.0000	
		(0.0001)	(0.0001)	
Wind Speed		0.0553	0.0236	
		(0.2380)	(0.2301)	
Wind Direction		-0.0001	-0.0001	
		(0.0016)	(0.0015)	
Child Age		0.0013		0.0014
		(0.0054)		(0.0053)
Refrigerator *(1=Yes)*		-0.0041		-0.0066
		(0.1618)		(0.1576)
Source of Drinking Water *(1=Improved)*		0.0009		0.0040
		(0.2034)		(0.2012)
Maternal Education Primary *(1=Primary)*		-0.7983**		-0.7907**
		(0.3714)		(0.3695)
Maternal Education Secondary *(1=Secondary)*		-0.1840		-0.1887
		(0.2571)		(0.2560)
Maternal Education Higher *(1=Higher)*		-0.1295		-0.1151
		(0.4313)		(0.4187)
Constant	-0.0029	-0.0007	-0.0648	0.1046
	(0.2762)	(0.6611)	(0.5937)	(0.4062)

Observations	934	934	934	934
R-squared	0.6095	0.6156	0.6096	0.6155
Weather Controls	No	Yes	Yes	No
WAZ-Related Controls	No	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

Notes: Temperature Bin 4 (24-28°C) is set as the reference bin. The coefficients of the other temperature bins represent the marginal effect on the probability of being underweight (i.e. WAZ <-2 SD) of an additional day in the nth temperature bin, relative to a day in the omitted bin (24-28°C). The controls Refrigerator, Source of Drinking Water and Maternal Education represent the share of observations with a value of 1 within district d in wave t. Robust standard errors in parentheses. *** Significant at the 1 percent level (p<0.1) ** Significant at the 5 percent level (p<0.05). * Significant at the 10 percent level (p<0.1).

8.4 Generative AI

This appendix provides a detailed account of the use of the Generative AI tool ChatGPT during the development and writing of this thesis. This tool was used to support coding, data analysis and to export tables from STATA to Word. All outputs generated were critically evaluated and, where necessary, modified by myself to align with the objectives of this research. I discussed with my supervisor that for the output of AI, I only include the parts in the appendix that I actually used, as the Generative AI tool ChatGPT can sometimes answer very elaborately.

Generative AI tool used: ChatGPT model o3 (based on GTP-4 series), that is provided by OpenAI.

Coding and Data Anlysis (1)

- **Description**:
    - Tool: ChatGPT
    - Purpose: To list the district codes to see if it was needed to place a command that only keeps the districts with district code below 801, which was needed to merge NFHS-4 and NFHS-5.
    - My Role: I used one of the commands to list district codes.
    - My reflection: It helped me to see if it was needed to place a command that only keeps the districts with district code below 801.
    - Applied in do-file.
- **Log of AI interaction**:
    - **Query to ChatGTP**: When I use data from NFHS-4, how can I see the labels of the variable district?
    - **Output from ChatGTP**:

To see the **labels of a variable** like district in **NFHS-4 data** (or any Stata dataset), you can use a few simple commands depending on what you mean by “labels”:

---

1. See value labels assigned to the variable

If district is a numeric variable with **value labels**, run:

stata

label list

This shows all the defined label sets in your dataset.

To see only the one attached to district:

stata

describe district

This tells you which value label (e.g., distlbl) is assigned to it under the "Value label" column.

Then:

stata

label list distlbl

That displays the mapping from numeric codes to district names.

- **How it was used**: The output was used to list district codes in order to see if it was needed to place a command that only keeps the districts with district code below 801.

Coding and Data Anlysis (2)

- **Description**:
  - Tool: ChatGPT
  - Purpose: To generate a variable which I could assign values to indicate what value label it has.
  - My Role: I used a part of the command and added some things to create the variable as assign the values.
  - My reflection: It helped me to create the variable I needed to identify the values of it.
  - Applied in do-file.
- **Log of AI interaction**:

- **Query to ChatGTP**: How to assign values (like ==0 when "poorest") to the numeric categorical variable wealth_index when it has value labels?
- **Output from ChatGTP**:

Great question! When your **numeric categorical variable** like wealth_index has **value labels**, and you want to assign new values **based on the label names** (e.g., set it to 0 if the label is "poorest"), you can do it in **Stata** using the label() function together with if.

Step-by-step example:

Let's say you want to create a new variable based on the **label names** of wealth_index. Here's how:

Step 1: Check the value labels

stata

label list

This shows you which value labels are assigned to wealth_index. For example:

stata

wealthlbl:

1 "poorest"

2 "poorer"

3 "middle"

4 "richer"

5 "richest"

Step 2: Create a new variable based on label text

Stata doesn’t let you directly compare the numeric variable to the label string (wealth_index == "poorest" won’t work), so you can:

Option A: Use decode and then compare:

stata

decode wealth_index, gen(wealth_str)

gen newvar = .

```
replace newvar = 0 if wealth_str == "poorest"
replace newvar = 1 if wealth_str == "poorer"
replace newvar = 2 if wealth_str == "middle"
replace newvar = 3 if wealth_str == "richer"
replace newvar = 4 if wealth_str == "richest"
```

  - **How it was used**: The output was used to generate a variable which I assigned values to indicate what value label it has.

Coding and Data Anlysis (3)

- **Description**:
  - Tool: ChatGPT
  - Purpose: To generate the variable to identify the districts.
  - My Role: I used the command to generate the variable to identify the districts, which were needed for merging.
  - My reflection: It helped me to prepare the data for merging.
  - Applied in do-file.
- **Log of AI interaction**:
  - **Query to ChatGTP (1)**: How to generate a variable called state_district that is a combination of the string variables state_name and district_name and make the letters small in STATA?
  - **Output from ChatGTP (1)**:

To generate a variable called state_district that combines the string variables state_name and district_name, and make all letters **lowercase**, you can do the following in **Stata**:

Step-by-step command:

stata

```
gen state_district = lower(state_name + "_" + district_name)
```

What this does:

- + "_" + adds an underscore between the state and district names.
- lower(...) converts the entire string to lowercase.
- gen creates the new variable state_district.

Example:

If:

- state_name = "Maharashtra"
- district_name = "Pune"

Then:

- state_district = "maharashtra_pune"

Let me know if you want to trim extra spaces or standardize the names further (e.g., removing special characters).

- **Query to ChatGTP (2)**: Yes trim them as well.
- **Output from ChatGTP (2)**:

Great! To combine state_name and district_name into a new variable state_district with:

- all lowercase letters,
- trimmed (no leading/trailing spaces), and
- an underscore _ between them,

use the following **Stata command**:

stata

```
gen state_district = lower(strtrim(state_name) + "_" + strtrim(district_name))
```

Explanation:

- strtrim(...) removes leading and trailing spaces.
- + "_" + adds the underscore between state and district.
- lower(...) makes the full result lowercase.
    - **How it was used**: The output was used to generate a variable that is a combination of the variables state_name and district_name, so I could identify the districts which I needed for merging. This was needed because some districts have the same name, but are located in different states.

Coding and Data Anlysis (4)

- **Description**:
    - Tool: ChatGPT
    - Purpose: Generate the commands to tell STATA a district-wave panel is used.
    - My Role: I used the commands, but changed it a bit.
    - My reflection: It helped me to start with the regressions since STATA needs to know what kind of panel it is.
    - Applied in do-file.
- **Log of AI interaction**:
    - **Query to ChatGTP**: How to tell STATA it is a district-wave panel where district is the string variable state_district and wave is wave?
    - **Output from ChatGTP**:

To set up a **district-wave panel** in **Stata**, where:

- state_district is a **string variable** identifying districts (like "MH_Pune", "UP_Lucknow", etc.), and

- wave is the **time variable** (e.g., 1, 2, 3...),

you need to convert the string variable into a **numeric panel ID** first, because xtset in Stata only accepts numeric panel identifiers.

Step-by-step:

1. **Encode the string variable into a numeric ID:**

stata

encode state_district, gen(district_id)

This creates a numeric variable district_id corresponding to your string district names.

---

2. **Set the panel structure:**

stata

xtset district_id wave

Now Stata knows that district_id is the **panel identifier**, and wave is the **time variable**.

  - **How it was used**: The output was used to change the string variable state_district into a numeric variable, and to tell STATA that a district-wave panel is used. It was adapted a little bit since district_id got a different name.

Coding and Data Anlysis (5)

- **Description**:
  - Tool: ChatGPT
  - Purpose: Generate the commands to create a histogram for the variable weight-for-age Z scores (WAZ).
  - My Role: I used the commands, but adjusted them in order to edit the histogram.

- My reflection: It helped me to add something to my histogram which made it more clear.
- Applied in appendix 8.1 for Figure 8.1.1.

- **Log of AI interaction**:
  - **Query to ChatGTP**: How to create a histogram of the variable WAZ_divided with red vertical lines at the value -2 and -3?
  - **Output from ChatGTP**:

To create a histogram of the variable WAZ_divided with **red vertical lines** at **-2** and **-3** in **Stata**, you can use the histogram command along with the addplot() option.

Here's the full command:

stata

```
histogram WAZ_divided, width(0.5) frequency ///
    addplot((line y1 x1, lcolor(red) lpattern(solid)) ///
            (line y2 x2, lcolor(red) lpattern(solid))) ///
       name(waz_hist, replace)
```

  - **How it was used**: The output was used to create a histogram with vertical lines for -2 and -3, after making some changes to the command.

Coding and Data Anlysis (6)

- **Description**:
  - Tool: ChatGPT
  - Purpose: The create command that create a figure of the average number of days in each temperature bin.
  - My Role: I used the commands, but adjusted them in order to edit the figure.
  - My reflection: It helped me to create the commands that create a clear figure of the average number of days in each temperature bin.
  - Applied in section 3.6 for Figure 3.6.2.
- **Log of AI interaction**:

- **Query to ChatGTP**: How to generate a bar graph of the average number of days in each temperature bin where bin 1 has temperature <16, bin 2 16-20, bin 3 20-24, bin 4 24-28 bin 5 28-32 and bin 6 >32?
- **Output from ChatGTP**:

To generate a **bar graph** of the **average number of days in each temperature bin** in **Stata**, you'll need to:

1. **Create the bins** from your temperature data.
2. **Count the number of days in each bin (per unit, if applicable)**.
3. **Calculate the average number of days per bin**.
4. **Plot a bar graph**.

Step-by-step:

(Optional: assign labels for nicer graph output)

stata

```
label define temp_bins 1 "<16°C" 2 "16–20°C" 3 "20–24°C" 4 "24–28°C" 5 "28–32°C" 6 ">32°C"

label values temp_bin temp_bins
```

Step 3: Plot the bar graph

stata

```
graph bar days, over(temp_bin, label(angle(45))) ///
    bar(1, color(navy)) ///
    title("Average Number of Days per Temperature Bin") ///
    ytitle("Average Days") ///
    blabel(bar, format(%9.0g))
```

- **How it was used**: The output was used to create commands that create a figure of the average number of days in each temperature bin.

Coding and Data Anlysis (7)

- **Description**:
  - Tool: ChatGPT
  - Purpose: Generate the commands to export tables from STATA to Word.
  - My Role: I used the commands, but adjusted them so they used my own variables.
  - My reflection: It helped me to export the tables to Word, which I could edit before putting them in my thesis.
  - Applied in appendix 8.1 for Table 8.1.1 and in appendix 8.2 for Table 8.2.1.
- **Log of AI interaction**:
  - **Query to ChatGTP**: What is the command to export tables from STATA to Word?
  - **Output from ChatGTP**:

To export tables from **Stata to Word**, there are a few ways to do it, depending on what kind of table you want to export (e.g., regression output, summary statistics). Here's the most common and effective method using the **asdoc** or **putdocx** command.

Option 1: Using asdoc (most user-friendly)

1. Install asdoc (if you haven't already):

stata

ssc install asdoc, replace

2. Use it to export output to Word:

For example, to export a regression:

stata

asdoc regress y x1 x2, replace

This creates a Word file (asdoc.doc) in your current working directory with the regression table.

You can specify a custom filename:

stata

```
asdoc regress y x1 x2, replace save(mytable.doc)
```

- **How it was used**: The output was used to export tables from STATA to Word, after adjusting the commands so they used my own variables.